Syndication, Interconnectedness, and Systemic Risk

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January 21, 2014

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Abstract

This paper studies the interconnectedness of banks in the syndicated loan market as a major source of systemic risk. We propose a novel measure of interconnectedness based on the "distance" (similarity) between two banks' syndicated loan portfolios. Collaboration in loan markets increases the overlap of banks' loan portfolio and makes them more vulnerable to contagious effects (such as asset price and liquidity risk). Interconnectedness is positively related to both bank size and level of diversification; however, diversification matters more than size. We find a positive correlation between interconnectedness and various bank-based systemic risk measures including S*RISK*, *CoVaR*, and *DIP*. That is, more heavily interconnected banks contribute more to systemic risk and this effect is exacerbated during recessions. Using a market-level measure of systemic risk, *CATFIN*, we also find that interconnectedness increases aggregate systemic risk during recessions.

Keywords: Interconnectedness, networks, syndicated loans, systemic risk

JEL Classifications: G20, G01

"Examples of vulnerabilities include high levels of leverage, maturity transformation, interconnectedness, and complexity, all of which have the potential to magnify shocks to the financial system."

– Ben S. Benanke, *Monitoring the Financial System*, 2013, p. 3.

1 Introduction

The financial crisis of 2007-2009 demonstrated how large risk spillovers among financial institutions caused a global systemic crisis and worldwide economic downturn. The collapse of the interbank market at the beginning of the crisis suggests an important channel of contagion among financial institutions through funding shocks (Gai et al. [19] and Gai and Kapadia [20]). A second important channel is commonality of asset holdings. As banks have similar asset portfolios, a decline in asset prices can spread throughout the banking system because of direct exposure of other banks to the same assets as well as induced correlations among assets due to, for example, fire sales (May and Arinaminpathy [30]).

While the theoretical literature emphasizes the importance of interconnectedness in the form of overlapping asset portfolios for understanding the vulnerability of the financial system (see, for example, Allen et al. [5]), the empirical literature provides little guidance. Neither does the Basel Committee include interconnectedness through the asset side of banks' balance sheets when identifying systemically important banks. However, commonality of assets among banks is of first order importance as indicated by Federal Reserve Chairman Bernanke in his speech at the Conference on Bank Structure and Competition in May 2010 in Chicago (Bernanke [9]):

> "We have initiated new efforts to better measure large institutions' counterparty credit risk and interconnectedness, sensitivity to market risk, and funding and liquidity exposures. These efforts will help us focus not only on risks to individual firms, but also on concentrations of risk that may arise through common exposures or sensitivity to common shocks. For example, we are now collecting additional data in a manner that will allow for the more timely and consistent measurement of individual bank and systemic exposures to syndicated corporate loans."

In this paper, we study this form of interconnectedness of financial institutions examining the organizational structure of loan syndicates. The syndicated loan market provides an ideal laboratory to study interconnectedness of banks. It is the most important market for corporate finance and its size exceeds the size of public debt and equity markets (Sufi [35]). Banks repeatedly participate with different percentage shares in syndicated loans arranged by one another. With borrower and lender identities available to us, we are able to track banks' investments in this market and quantify the overlap of their assets over time.

We develop a novel measure of interconnectedness for which the key component is the "distance" (similarity) between two banks' syndicated loan portfolios. Such a distance measure is computed as the Euclidean distance between two banks based on their loan portfolio weights in each area of specializations, that is, borrower industries and locations. It measures interconnectedness that "can arise from common holdings of assets or through the exposure of firms to their counterparties" (Bernanke [10]). First of all, the distance measure is a *direct* measure of interconnectedness: Less distant banks have more similar loan portfolios and thus have a higher exposure to common shocks. Second, there is a high propensity of bank lenders to concentrate syndicate partners rather than to diversify them as lead arrangers choose participant lenders that are closer in terms of specializations, i.e., those that are already more connected through similar loan portfolios as lead arrangers themselves. The distance measure is thus also an *indirect* measure of interconnectedness: Closer banks are more likely to collaborate in future loans and to increase their interconnectedness. As a result, even though this behavior can benefit both syndicate lenders and borrowers under normal circumstances, it may as well create negative externalities during crises as banks become systemic.

In order to measure interconnectedness for a particular bank, we take the weighted average of distance between one bank and all the other lead arrangers in the syndicated loan market. The weights can be either the market shares of (i.e., size-weighted) or the proportions of interbank relationships with all the other lead arrangers (i.e., relationship-weighted). Since distance is negatively related to interconnectedness (smaller distance meaning higher interconnectedness), we linearly transform the weighted average of distance into an interconnectedness measure such that it is normalized to a scale of 0-100 with 0 being the least interconnected and 100 being the most interconnected. We then create a monthly Interconnectedness Index aggregated at the market level by taking the weighted average of interconnectedness at the individual bank level. The weights adopted for computing the market-aggregate index are the market shares of all the lead arrangers in the market.

Next, we investigate potential determinants of interconnectedness and find that bank size (which is a bank's market share as a lead arranger in the syndicated loan market), level of diversification, and number of specializations are all significantly and positively correlated with its interconnectedness. However, our results suggest that diversification matters more than bank size, partly mitigating concerns that our results reflect size effects. The time series of the market-aggregate Interconnectedness Index shows a clear jump in interconnectedness from 1989 to 1994, primarily due to the fast growth of the syndicated loan market and an increase in bank players in this market. Nevertheless, our results are not sensitive to whether the sample is from the pre- or post-1995 period. In addition, interconnectedness dropped significantly during the period from mid-2008 to the end of 2009, but it has risen again and returned to the peak level before the crisis.

A greater interconnectedness measure indicates higher vulnerability to common or systemic shocks. This vulnerability arises not only because of the risk of adverse asset price movements but also externalities of interconnectedness that lead to funding liquidity risk if short-term investors decide not to rollover and withdraw funds from these institutions (Allen et al. [5]).

First, the pattern of collaboration in the syndicated loan market increases the overlap of loans on the balance sheets of the participating banks, which increases their exposure to common shocks and decreases the diversity among banks. Diversification helps banks reduce their individual default risk because the impact of small shocks to individual banks (as they usually occur in economic upswings) is mitigated. However, in a severe financial crisis such as the crisis from 2007 to 2009, the lack of diversity among banks increases the vulnerability of the financial system. In a systemic shock, selling-off assets can lead to mark-to-market losses for banks holding similar exposures. Moreover, higher asset price volatility might lead to tighter margins forcing other banks to liquidate assets jointly causing a further drop in asset prices and an increase in liquidation costs. In other words, at the same time as banks diversify their individual loan portfolios, overall risk is contained within this network, and the increasing interconnectedness of banks intensifies the sensitivity of these banks to aggregate fluctuations.

Second, spillovers can arise as externalities because banks finance illiquid assets (such as loans) largely with short-term debt. If banks need to liquidate these assets in times of crises, short-term investors of other institutions with similar exposures might refuse to rollover short-term funding or engage in precautionary liquidity hoarding (Acharya and Skeie [3]) increasing funding risks of these institutions.

In the final part of the paper, we test this empirically relating interconnectedness to various measures of systemic risk. Similar to approaches used in stress tests that have been conducted in the U.S. and Europe since 2008, the construction of these measures is to estimate losses in a stress scenario and determine a bank's equity shortfall after accounting for these losses. These measures capture asset price as well as funding liquidity risks associated with interconnectedness using market data.

The literature on systemic risk proposes different measures that quantify spillover effects among financial institutions in a systemic crisis using different tail risk metrics. First, developed by Acharya et al. [2] and Brownlees and Engle [12], SRISK measures the equity capital shortfall of a bank if the overall market declines by 40% over a 6-months period and assuming a regulatory capital ratio of 8%. Second, developed in Adrian and Brunnermeier [4], *CoVaR* measures the difference between the *VaR* of the financial system conditional on an individual institution being in distress and the *VaR* of the financial system conditional on the median state of the same institution. Third, *DIP* is a distressed insurance premium to cover losses that exceed a certain threshold of a bank's liabilities (Black et al. [11], Huang et al. [24], and Huang et al. [25]). While these three methods construct bank-specific systemic risk measures, we use also a measure for the overall systemic risk of the banking sector called *CATFIN* (Allen et al. [6]).

An interesting difference among *SRISK*, *CoVaR*, and *DIP* is directionality. While *CoVaR* measures the value at risk (*VaR*) of the financial system conditional on any single bank being in distress, the other two measure which banks are most exposed conditional on the financial system being in distress. Importantly, however, all three concepts measure a co-movement of asset prices without the notion of causality. In other words, a bank can contribute to systemic risk of the financial system because it causes systemic risk or because of common factor exposure. Moreover, all measures are constructed to estimate cross-sectional differences in systemic risk at a point of time.

We find a positive and significant correlation between our interconnectedness measure and various systemic risk measures including *SRISK*, *CoVaR*, and *DIP*. Using a multivariate setting, we further show that an increase in a bank's interconnectedness also increases the systemic risk contribution of the bank. Another way of interpreting this result is that indirect interconnectedness of banks is a useful tool to forecast cross-sectional differences in systemic risk if a severe crisis occurs. Various tests suggest that our results are consistent across different systemic risk measures and model specifications. This relationship is particularly strong during recessions.

At the market aggregate level, interconnectedness also elevates the bank sector systemic risk measure, *CATFIN*, during recessions. It suggests that diversification benefits brought by the syndication process are accompanied with important negative externalities that will eventually lead to enhanced systemic risk during crises. In other words, interconnectedness magnifies the consequences of a systemic crisis.

Our paper contributes to the existing literature along a number of dimensions. First, we extend the network literature by constructing a novel empirical measure of interconnectedness among banks. Second and relatedly, we measure interconnectedness among banks based on overlapping loan portfolios. Most of the prior literature measures interconnectedness on the liability side through interbank markets for short-term purchased funds. While common bank asset-side exposure has been widely recognized as an important channel of systemic risk, its relevance remains largely underexplored and the literature has not yet proposed empirical measures. We explore increasing interconnectedness on the asset side through similar exposures of banks to syndicated corporate loans. Third, we provide a comparison among various systemic risk measures (*SRISK*, *CoVaR*, *DIP*, and *CATFIN*) which have been suggested in the literature. Fourth, we link the literature on "networks" to the literature that develops empirical measures that assess the systemic risk of financial institutions. We show empirically that common exposures to corporate loans can be used to forecast cross-sectional differences in systemic risk contributions of banks.

Overall, our paper also relates to several strands of existing literature. It relates to the theoretical literature on networks (Cifuentes et al. [17], Beale et al. [8], Gai et al. [19], and Allen et al. [5]). Cifuentes et al. [17] model a liquidity spiral of interconnected banks due to mark-to-market accounting of illiquid assets when banks are subject to regulatory capital constraints. They show that even small shocks can lead to contagious failures. Beale et al. [8] model a network of banks with overlapping asset portfolios. The authors find that banks should diversify (but in different asset classes) if systemic costs are large. Gai et al. [19] construct a network of banks linked through their interbank market exposures. They identify as the cause market failure those banks that do not internalize the effect of liquidity hoarding on other institutions. Relatedly, Allen et al. [5] find that contagion is more likely in clustered networks when bank debt is short-term. We construct a new empirical proxy to measure the interconnectedness of banks through large syndicated loans and show that this interconnectedness increases systemic risk.

Allen and Gale [7] show in their seminal paper that a more complete network structure makes the financial system more resilient to an unanticipated aggregate liquidity shock. Brusci and Castiglionesi [13] show that this result breaks down if the liquidity shock is anticipated. These results together suggest that the effect of interconnectedness is ambiguous. Moreover, Gai and Kapadia [20] find a tipping point in interconnectedness below which more interconnectedness is stabilizing and above which it is destabilizing using methods from the epidemiology literature. Acemoglu et al. [1] find similar results. We add to this literature by providing an additional dimension of interconnectedness through banks' common engagement in syndicated lending.

Our paper is also related to the theoretical literature that analyzes the effect of diversification on portfolio risk (Shaffer [32], Wagner [37], and Ibragimov et al. [26]). A common notion in these papers is their emphasis on the limits of diversification. While financial institutions reduce their idiosyncratic risks through loan diversification via participation in syndicated loans originated by other banks, they increase systemic risk because their loan portfolios become more similar. Our paper is an empirical complement to these theory papers. Diversification is an important motive for banks to syndicate loans to other banks (Simons [33]). However, our analysis shows that loan portfolios of participating banks become more similar, which increases their systemic risk.

Finally, our paper relates to the empirical literature on the growth of syndicated lending. During the last decade, a fast growing literature has looked at various aspects of the structure of the syndicated loan market.[1] The market for syndicated loans has grown extremely rapidly since 1989. Figure 1 shows the growth of this lending on an annual basis. Note that even in the 2007 – 2009 crisis years, its size was still extremely large. A possible explanation is the benefits to lenders from being able to syndicate large corporate loans. Syndicating, i.e. selling a large proportion of loans that banks originate themselves or participating in loans to borrowers banks usually do not

[1] Among others, Chowdhry and Nanda [16], Pichler and Wilhelm [31], and Tykvová [36] theoretically analyze the rationale for syndication and find that syndicates are formed for reasons such as risk sharing, knowledge transfer, and regulation circumventing. Empirical papers on syndicated loans have examined syndicate structure from the perspectives of information asymmetry (e.g., Jones et al. [28], Lee and Mullineaux [29], and Sufi [35]), lenders' reputation (e.g., Dennis and Mullineaux [18], and Gopalan et al. [22]), reciprocal arrangements (e.g., Cai [14]), and liquidity management (e.g., Gatev and Strahan [21]). The effect of information asymmetry and liquidity has also been studied in syndicated loan pricing (e.g., Gupta et al. [23], and Ivashina [27]).

have access to, helps them diversify their loan portfolio. Moreover, the development of the syndicated loan market accommodates the financing needs of large borrowers. Banks face regulatory restrictions such as single counterparty exposure limits as well as regulatory capital requirements that inhibit individual banks from regularly financing large loans to large firms. The development of the syndicated loan market allows banks to continue lending to and thus building relationships with large firms. Similarly, banks are able to reduce capital requirements as syndication removes part of the credit risk associated with the loan from the bank's balance sheet.

None of the above academic studies, however, discusses the trade-off between the benefits associated with syndicated lending and the costs when economic conditions worsen. In our paper, we compare portfolio holdings of lenders in the syndicated loan market, measure their interconnectedness, and then study the implications of interconnectedness for systemic risk among banks.

The paper proceeds as follows. In Section 2, we lay out our empirical methodology, in particular, derive our measures of distance and interconnectedness, and discuss various systemic risk measures as well as the related literature. Data used in this study are described in Section 3 with summary statistics for our sample of syndicated loan facilities as well as various distance, interconnectedness, and systemic risk measures. Sections 4 and 5 discuss our empirical results on interconnectedness in loan syndications and the implications of such interconnectedness for systemic risk. Finally, we conclude in Section 6 with some policy implications.

2 Empirical Methodology

In this section, we develop our loan portfolio interconnectedness measure and show how it can be used for an empirical analysis of systemic risk. First, we describe how the distance between two banks based on lending specializations - specifically borrower industry and location - is measured. Then, we explain how we construct our interconnectedness measure at the individual bank level, as well as at the aggregate market level, based on these distance measures. In order to understand the determinants of interconnectedness, we also construct a measure of diversification at the bank level and use the Herfindahl index as a proxy for market competitiveness. We then provide a brief summary of four systemic risk measures that have been proposed in the recent literature: (i) systemic capital shortfall (*SRISK*), (ii) contagion value-at-risk (*CoVaR),* (iii) distress insurance premium (*DIP*), and (iv) *CATFIN*. While the first three measures are bank specific, *CATFIN* is an aggregate measure of systemic risk of the overall banking sector. We then examine how interconnectedness relates to each of them. All variables are defined in Appendix 1.

2.1 Measuring Interconnectedness

2.1.1 Distance between Two Banks

We focus our analysis on the U.S. syndicated loan market, that is, syndicated loans extended to U.S. firms. Six proxies for bank syndicated loan specializations are employed related to either borrower industry or borrower geographic location. Specifically, we use the borrower SIC industry division[2], the 2-digit, 3-digit, and 4-digit borrower SIC industry, the state where the borrower is located[3], and the 3-digit borrower zip code to examine in which area(s) each bank has heavily invested.[4] We then compute the distance between two banks by quantifying the similarity of their loan portfolios. The detailed construction of our distance measure is as follows.

First, based on DealScan's loan origination data, for each of the months from January 1989 to July 2011, we rank lead arrangers by the total loan facility amounts originated during the prior 12 months.[5] There were roughly 100-180 active lead arrangers each month; as a result, we obtain a total of 37,311 unique lead arranger-months. Then, we compute portfolio weights for each lead arranger in each specialization category (e.g., 2-digit borrower SIC industry). Let $w_{i,j,t}$ be the weight lead arranger *i* invests in specialization (i.e., industry or location) *j* within 12 months prior to month *t*.[6] Note that for all pairs of *i* and *t*, $\sum_{j=1}^{J} w_{i,j,t} = 1$, where *J* is the number of industries

[2] The SIC industry division is defined with a range of 2-digit SIC industries (see Appendix 2 for detail) whereas 2-digit SIC indicates the major group and 3-digit SIC indicates the industry group.
[3] The 3-digit zip code refers to the first three digits of the U.S. zip code, which designate a sectional center facility, the mail-sorting and -distribution center for an area. With the first digit of the zip code representing a group of U.S. states and the second and third digits together representing a region or a large city in that group, these three digits combined pinpoint a more specific geographic location than states.
[4] Borrower geographic location is determined by the address of the borrowing firm's headquarter. As financing decisions, especially those related to issuing large amounts of debt such as syndicated loans, are made by a firm's finance department typically located at its headquarter, it is reasonable to assume that banks work with their clients' headquarters instead of satellite offices at other locations.
[5] Loan amount is split equally over all lead arrangers for loans with multiple leads.
[6] We consider the portfolio of syndicated loans originated during the previous 12 months the best representation of a bank's lending specializations. Results of our paper still hold if we extend this 12-month period to the mean/median loan maturity, which is 48 months.

or locations the lender can be specialized in. For example, for the 2-digit borrower SIC industry, *J* can be as many as 100.

Next, we compute the distance between two banks as the Euclidean distance between them in this *J*-dimension space.[7] Let $Distance_{m,n,t}$ be the distance between banks *m* and *n* in month *t*, where $m \neq n$. Then

$$Distance_{m,n,t} = \sqrt{\sum_{j=1}^{J} \left(w_{m,j,t} - w_{n,j,t}\right)^2}. \tag{1}$$

Appendix 2 provides an example on how distance is computed between two banks as specified in (1). We show the computation of distance based on borrower SIC industry division among three lead arrangers in Appendix 2 – JPMorgan Chase, Bank of America, and Citigroup – that were ranked the top three as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months (i.e., January-December 2006). Based on our distance measures Citigroup had a different loan portfolio from those held by either JPMorgan Chase or Bank of America, investing more heavily in the manufacturing, transportation, communications, electric, gas, sanitary, and services industries and less heavily in retail trade, finance, insurance and real estate. As a result, the distance computed between Citigroup and either JPMorgan Chase or Bank of America is greater than the distance between JPMorgan Chase and Bank of America whose portfolios were more similar to each other. Appendix 3 summarizes the pairwise distance among the top ten lead arrangers as of January 2007. Note that he distance measure must lie within the range of 0 to $\sqrt{2}$ due to the definition of Euclidean distance.

2.1.2 Bank-level Interconnectedness

In order to measure the interconnectedness at the bank-level, we first take the weighted average of the distance between a given lead arranger and all other lead arrangers in the syndicated loan market. As a smaller Euclidean distance means higher interconnectedness, we then linearly transform the weighted average of distance into an interconnectedness measure for the bank such

[7] The Euclidean distance is the square root of the sum of the squared differences in portfolio weights across all dimensions of lending specializations.

that it is normalized to a scale of 0-100 with 0 being least interconnected and 100 being the most interconnected. That is, a higher number indicates a more interconnected bank. More specifically, the interconnectedness of bank i in month t, $Interconnectedness_{i,t}$ equals:

$$Interconnectedness_{i,t} = \left(1 - \frac{\sum_{i \neq k} x_{i,k,t} \cdot Distance_{i,k,t}}{\sqrt{2}}\right) \times 100, \tag{2}$$

where $d_{i,k,t}$ is the distance between bank i and bank k in month t as defined in (1), and $x_{i,k,t}$ is the weight given to bank k in the computation of bank i's interconnectedness. Two kinds of weights are adopted here. The first weight is the overall syndicated loan market share of bank k, based on which we obtain a "size-weighted interconnectedness" measure. The second weight is the proportion of collaborative relationships between bank i and bank k in the total number of such relationships bank i had with lead arrangers (including bank k) in the syndicated loan market during the prior twelve months. A collaborative relationship is identified if bank j is bank i's participant lender, co-lead, or lead arranger. This second approach to weighting gives us a bank "relationship-weighted interconnectedness" measure. The two alternative weighting approaches allow us to examine interconnectedness along different dimensions, so that our results are unlikely to be driven solely by either size or bank relationships.

2.1.3 Market-aggregate Interconnectedness

Next, we construct a monthly Interconnectedness Index aggregating bank-level interconnectedness to the market level. This market-aggregate interconnectedness measure is computed by taking the weighted average of interconnectedness of individual banks. The market shares of all the lead arrangers that have been in the syndicated loan market during the prior twelve months are used as weights. Then, the market-aggregate Interconnectedness Index in month t, $Interconnectedness\ Index_t$, is:

$$Interconnectedness\ Index_t = \sum_i y_{i,t} \cdot Interconnectedness_{i,t}, \tag{3}$$

where $Interconnectedness_{i,t}$ is the interconnectedness of bank *i* as defined in (2) above and $y_{i,t}$ is the market share of bank *i* based on its syndicated loan portfolio during the previous twelve months. We use the market share as the weight for each bank to account for the size effect on the overall level of interconnectedness. Intuitively, the larger the bank, the more it contributes to the aggregate interconnectedness of the entire syndicated loan market.

2.1.4 Diversification and Competitiveness

Diversification is an essential vehicle for banks to reduce risk. Thus, loan syndication can help a bank to diversify its asset portfolio. We construct the following diversification measure for banks to understand how loan portfolio diversification interacts with interconnectedness. Let $Diversification_{i.t}$ measure the diversification level of bank *i* in month *t*. Then:

$$Diversification_{i,t} = \left[1 - \sum_{j=1}^{J} \left(w_{i,j,t}\right)^2\right] \times 100, \tag{4}$$

where, as in (1), $w_{i,j,t}$ is the weight lead arranger *i* invests in specialization *j* (i.e. industry or geographical area) within 12 months prior to month *t*. The notion behind the measure is that as a bank becomes more diversified, $\sum_{j=1}^{J}\left(w_{i,j,t}\right)^2$ becomes smaller, so that the measure for diversification grows larger.

Another important measure is the competitiveness of the syndicated loan market, and we use a Herfindahl index to proxy for market competitiveness. This index is constructed as follows:

$$Herfindahl_t = \sum_{i} \left(y_{i,t}\right)^2 \times 100, \tag{5}$$

where, as in (3), $y_{i,t}$ is the market share of bank *i* in the syndicated loan market based on its portfolio during the twelve-month period prior to month *t*. As is well known, the more competitive the syndicated loan market, the smaller the Herfindahl index will be.

Note that the interconnectedness measure, the diversification measure, and the Herfindahl index are all constructed to have the scale of 0-100.

2.2 Measuring Systemic Risk

To analyze the link between loan portfolio interconnectedness and systemic risk, we use four measures proposed in the prior literature: (i) systemic capital shortfall (*SRISK*), (ii) contagion value-at-risk (*CoVaR*), (iii) distress insurance premium (*DIP*), and (iv) *CATFIN*. These measures are described briefly below.

2.2.1 *SRISK*

SRISK is a bank's US-Dollar capital shortfall in the advent of a systemic crisis which is defined as a 40% decline in aggregate banking system equity over a 6-month period. This measure is developed in Acharya et al. [2] and Brownlees and Engle [12].[8] *SRISK* is defined as

$$\begin{aligned} SRISK &= E\big((k(D+MV)-MV)\big|\text{Crisis}\big) \\ &= kD-(1-k)(1-LRMES)MV, \end{aligned} \tag{6}$$

where D is the book value of debt that is assumed to be unchanged over the crisis period, *LRMES* is the long-run marginal expected shortfall and describes the co-movement of a bank with the market index when the overall market return falls by 40% over the crisis period.[9] $LRMES \times MV$ is the expected loss in market value of a bank over this 6-month window. k is the prudential capital ratio which is assumed to be 8% for U.S. banks and 5.5% for European banks to account for accounting differences between US-GAAP and IFRS. *SRISK* thus combines both the firm's projected market value loss due to its sensitivity with market returns and its (quasi-market) leverage.[10] Naturally, *SRISK* is greater for larger banks. To make sure that our results are not driven by solely bank size, we conduct various tests. For example, we perform analyses using only *LRMES* which essentially is a tail risk rather than a size measure. Moreover, our alternative systemic risk proxies do not incorporate leverage to the same extent as *SRISK*.

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[8] The results of this methodology are available on the Volatility Laboratory website (V-Lab), where systemic risk rankings are updated weekly both globally and in the United States (see http://Vlab.stern.nyu.edu/). V-Lab provides the data for about 100 U.S. and 1,200 global financial institutions.

[9] V-Lab uses the S&P 500 for U.S. banks and the MSCI ACWI World ETF Index for European banks.

[10] A quasi-market leverage includes book value of debt plus market value of equity minus book value of equity.

While *SRISK* provides an absolute shortfall measure, it can also be expressed to reflect a bank's contribution to the shortfall of the financial system as a whole (or aggregate *SRISK*). This measure is called *SRISK%* and is constructed by dividing *SRISK* for one bank by the sum of *SRISK* across all banks at each point in time.

2.2.2 *CoVaR*

Developed in Adrian and Brunnermeier [4], *CoVar* is the *VaR* of the financial system conditional on one institution being in distress and Δ*CoVar* is the marginal contribution of that firm to systemic risk. The *VaR* of each institution is measured using quantile regressions and the authors use a 1% and 5% quantile to measure *CoVaR*:

$$\text{Prob}\left(L \geq CoVaR_q \middle| L^i \geq VaR_q^i\right) = q, \tag{7}$$

where L is the loss of the financial system, L^i the loss of institution i and q is the VaR quantile (for example, 1%). *CoVaR* measures spillovers from one institution to the whole financial system. Importantly, *CoVaR* does not imply causality, i.e. it does not imply that a firm in distress causes the systemic stress of the system, but rather suggests that it could be both, a causal link and/or a common factor (in terms of asset or funding commonality) that drives a bank's systemic risk contribution.

CoVaR is not explicitly sensitive to size or leverage such as *SRISK*. Moreover, in contrast to *SRISK*, *CoVaR* only includes the correlation with market return volatility and not a bank's return volatility. Suppose that two banks have the same market return correlation but bank A has low volatility while bank B has a high volatility. Both banks would have the same *CoVaR* even though bank A is essentially low risk.

2.2.3 *DIP*

The distressed insurance premium (*DIP*) measure has been proposed by Huang et al. [24] and Huang et al. [25] and applied to evaluate systemic risk in the European banking sector by Black et al. [11]. *DIP* is a hypothetical insurance premium to cover losses that exceed a certain threshold of total banks' liabilities and can be expressed as follows:

$$DIP = \mathrm{E}^{Q}\big(L \times 1(L \geq L_{min})\big), \tag{8}$$

where L is the total liabilities of the banking sector and L_{min} is the threshold as a measure of financial distress. The most important input factors are a bank's probability of default *PD* (which is derived from CDS spreads) and asset correlations. Under a constant debt assumption over the measurement period, asset correlations are measured using equity correlations among banks. The *PDs* are used to calculate default thresholds for all banks. The authors simulate asset values and define a default event when the asset value falls below this default threshold. Historical loss given default (*LGD*) values are used to derive a loss distribution which in turn is used to derive the likelihood that $L \geq L_{min}$. Finally, the *DIP* measure is constructed multiplying this probability with the expected losses in case of a systemic crisis.

2.2.4 *CATFIN*

Our fourth measure to link interconnectedness to systemic risk is the *CATFIN* measure developed by Allen et al. [6]. While *SRISK*, *CoVaR* and *DIP* measure the cross-sectional differences in banks' contribution to systemic risk (or micro / bank-level measures of systemic risk), *CATFIN* is an aggregate measure of systemic risk in the financial sector. Allen et al. [6] show that micro-level measures are helpful in explaining the cross-sectional variation in systemic risk contributions; however, they do a poor job in forecasting macroeconomic developments. They develop *CATFIN* to forecast potential detrimental effects of financial risk taking by the overall financial sector on the macroeconomy. The intuition is that banks do not internalize the costs on the society when making risk-taking decisions and *CATFIN* is supposed to capture these externalities.

CATFIN is a value-at-risk (*VaR*) measure and is constructed as an unweighted average of three (parametric and non-parametric) *VaR* measures. This measure captures the system-wide level of risk taking and is calculated using the historical distribution of equity returns.

Taken together, we employ four different proxies to capture risks to the stability of the financial system as a whole. Importantly, as explained above, *SRISK*, *CoVaR*, and *DIP* are estimates of the co-variation between individual banks and systemic risk. *CATFIN*, on the other hand, is an aggregate measure for the overall banking sector systemic risk.

3 Data and Summary Statistics

In this section, we first briefly describe our data sources. We then provide summary statistics regarding lenders, borrowers, syndicated loan facilities, and the various measures developed or introduced in Section 2 above related to distance, interconnectedness, and systemic risk.

3.1 Data Sources

To analyze the interconnectedness of banks in loan syndication and how such interconnectedness affects banks' systemic risk, two primary sources of data are used: (i) syndicated loan data and (ii) systemic risk data. We obtain detailed loan information to construct the distance, interconnectedness, and diversification measures for lead arrangers from the DealScan database of loan syndications. The authors who proposed the *SRISK*, *CoVaR*, *DIP*, and *CATFIN* measures kindly provided us data on their respective systemic risk measures.

3.1.1 Syndicated Loans

Thomson Reuters LPC DealScan is the primary data base on syndicated loans with comprehensive coverage, especially in the U.S. market. We obtain a sample of 91,715 syndicated loan facilities originated for U.S. firms between 1988 and July 2011.

Interconnectedness is measured at the lead arranger (bank holding company) level. A lender is classified as a lead arranger if its "LeadArrangerCredit" field indicates "Yes." If no lead arranger is identified using this approach, we define a lender as a lead arranger if its "LenderRole" falls into the following fields: administrative agent, agent, arranger, bookrunner, coordinating arranger, lead arranger, lead bank, lead manager, mandated arranger, and mandated lead arranger.[11] Note that the "LeadArrangerCredit" and "LenderRole" fields generate similar identifications of lead arrangers.

DealScan data can only be manually matched with Compustat data. In doing so, we are able to retrieve financial data from Compustat for borrowers of 42,009 loan facilities (46% of our loan sample). Importantly, however, Compustat data are only used to provide additional descriptive

[11] See Standard & Poor's *A Guide to the Loan Market* [34] for descriptions of lender roles.

statistics regarding our sample and are not directly used in our empirical measure of interconnectness.

3.1.2 Systemic Risk

We obtain the *SRISK* data from NYU V-Lab's Systemic Risk database and the *CoVaR*, *DIP*, and *CATFIN* data from the authors who proposed them as systemic risk measures.

SRISK data covers 132 global financial institutions and 16,258 bank-months ranging from January 2000 to December 2011. We are able to match them with 5,799 lead arranger-months and 62 unique lead arrangers.

The *CoVaR* data are quarterly covering 1,194 public U.S. financial institutions, of which 44 can be found in our interconnectedness data as lead arrangers in the syndicated loan market. The *CoVaR* data are available from the third quarter of 1986 to the fourth quarter of 2010, and the matched sample includes 1,767 unique lead arranger-quarters.

The *DIP* data are weekly covering 57 unique European financial institutions from January 2002 to January 2013. We aggregate weekly data into monthly measures and obtain 5,235 bank-months with *DIP* measures. We are able to construct a matched sample of 22 unique lead arrangers and 1,414 lead arranger-months with our interconnectedness data.

Appendix 4 lists lead arrangers for which the various systemic risk measures are available.

The *CATFIN* data are monthly and available at the aggregate market level from January 1973 to December 2009. We match them with our monthly market-aggregate Interconnectedness Index and obtain a matched sample of 252 months.

3.2 Summary Statistics

3.2.1 Lead Arrangers, Borrowers, and Loans

Table 1 presents the characteristics of lead arranger, borrowers and loans based on the 91,715 syndicated loan facilities in our sample. Panel A of Table 1 reports lead arranger characteristics. We have 37,311 unique lead arranger-months. An average lead arranger has a market share of 0.73% and arranges 35 loan facilities, which correspond to an average volume of $6.67 billion of originated loans, during the previous twelve months.

Panel B of Table 1 reports borrower characteristics of 91,715 unique loan facilities. An average borrowing firm in our sample has sales of $2.8 billion at loan closing. Sixty percent had previously borrowed from the syndicated loan market at least once, and the average number of previous syndicated loans among all the borrowers is 2.4 loan facilities. Among borrowers whose firm type is known, 37% are identified as private firms, whereas 28% are public firms without bond ratings and 34% are public firms with bond ratings.

Among borrowers where Compustat data are available, the average book value of total assets is $11 billion, the average book leverage ratio is 37%, the average earnings to assets ratio is 6%, and 49% have S&P debt ratings of which 55% have an investment-grade rating.

Panel C of Table 1 shows characteristics of 91,715 syndicated loan facilities in our sample. An average syndicated loan facility has a size (loan amount) of $236 million and maturity of 48 months. The average all-in spread on drawn funds is 233 basis points over LIBOR. About one-third (32%) of the facilities are classified as term loans. On average, there are 7 lenders in one syndicate, and the lead arrangers retains 36% of the loan. The most common reason for borrowing is working capital or corporate purposes (62%), followed by acquisitions (23%), refinancing (22%), and backup lines (7%).[12]

3.2.2 Distance, Interconnectedness, and Systemic Risk

Table 2 reports summary statistics of the distance, interconnectedness, and systemic risk measures we described in section 2. Panels A and B summarize distance between 5,223,284 lead arranger pair-months and interconnectedness of 37,311 lead arranger-months, respectively, across the six lender specialization categories, i.e., the borrower's SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, the borrower state, and the borrower's 3-digit borrower zip code. Panel B reports both size- and relationship-weighted interconnectedness measures. While distance must lie within the range of 0 to $\sqrt{2}$ and our interconnectedness index must be within 0 and 100 by definition, the standard deviations of these measures – 0.3-0.4 for distance measures and 17-28 for interconnectedness measures – implies that there is sufficient variation for empirical tests. Further, the distributions of our distance as well as size- and relationship-weighted interconnectedness measures across different specialization categories are similar to one another,

[12] A loan facility can state more than one purpose for borrowing.

which indicates that our measures capture both distance and interconnectedness in a similar fashion. One notable difference, though, is that relationship-weighted interconnectedness tends to be somewhat smaller than its size-weighted counterpart and also has greater variation.

Panel C of Table 2 reports the summary statistics of *SRISK*, *CoVaR*, and *DIP* at the lead arranger level. Of the 5,799 matched lead arranger-months, the average *SRISK* is $25.7 billion, *SRISK*% 2.57%, and *LRMES* 3.81%, and a market leverage ratio of 18%. Of the 1,767 matched lead arranger-quarters, the 1% *CoVaR* is a decline of 2.31% or $15.4 billion of bank equity on average and the 5% *CoVaR* is a decline of 1.98% or $12.5 billion of bank equity on average.[13] Of the 1,414 matched lead arranger-months, the average DIP is 14.7 billion euros. All these measures show greater systemic risk for our sample of lead arrangers than an "average" financial institution in the *SRISK*, *CoVaR*, and *DIP* data sets.[14]

The *SRISK* measures (*SRISK*, *SRISK%*, and *LRMES*) and *CoVaR* measures (1% and 5%) have correlations ranging from 0.2 to 0.4 for the sample of lead arrangers that have the full data available. The correlation between *DIP* and *SRISK* is close to 0.8, whereas *DIP*'s correlation with *SRISK%* and *LRMES* is approximately 0.3.

4 Interconnectedness of Banks in Loan Markets

In this section, we first show empirically how banks connect in the syndicated loan market. Then we explore what drives the interconnectedness of a bank. Finally, we examine the time trend in the market-aggregate Interconnectedness Index.

4.1 Collaboration in Loan Syndicates

If two lead arrangers have small distance as measured in (1), it means that they have similar asset allocations in their corporate loan portfolios. In other words, they have high exposures to common shocks because of common corporate exposures. To understand the role of syndication in

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[13] The *CoVaR* data are all expressed in the form of losses, i.e., negative numbers. In our empirical analyses, we multiply *CoVaR* with minus one. I.e., a higher *CoVaR* implies higher systemic risk.

[14] For example, an average financial institution in the NYU V-Lab database has *SRISK* of $10.3 billion and *SRISK%* of 1.32%. An average public U.S. financial institution in the *CoVaR* data shows a decline of 1.15% or $0.785 billion at 1% *CoVaR*, and an average European financial institution in the *DIP* data shows a *DIP* of 10.9 billion euros.

producing similarity of corporate loan exposures, we examine the determinants of a bank's syndicated loan membership.

In order to make the data and computations manageable, we limit our interest to the top 100 lead arrangers in each month who held an aggregated share of 99.5% or more of the total market. We estimate the following regression:

$$Syndicate\ Member_{m,n,k,t} = \alpha + \beta_1 \cdot Distance_{m,n,t} + \beta_2 \cdot Lead\ Relationship_{m,n,t}$$
$$+\beta_3 \cdot Borrower\ Relationship_{n,k} + \beta_4 \cdot Market\ Share_{n,t} + Loan\ Facility_k' + e_{m,n,k,t}, \tag{9}$$

where the dependent variable $Syndicate\ Member_{m,n,k,t}$ is an indicator variable that equals one if lead arranger *m* chooses lender *n* as a member in loan syndicate *k* that is originated in month *t* and zero otherwise. The key independent variable $Distance_{m,n,t}$ measures the distance between lead arranger *m* and lender *n* based on their syndicated loan portfolios during the twelve months prior to month *t*. As a proxy for bank to bank relationships, $Lead\ Relationship_{m,n,t}$ is an indicator variable for whether lead arranger *m* had syndicated any loans with lender *n* prior to the current loan (no matter what roles the two lenders took). As a proxy for bank to firm relationships, $Borrower\ Relationship_{n,k}$ is an indicator variable for whether lender *n* arranged or participated in any syndicated loans that were made to the borrower prior to loan syndicate k. By including $Lead\ Relationship_{m,n,t}$ and $Borrower\ Relationship_{n,k}$ in the regression, we control for the effects of prior relationships between the two lenders and prior relationships between the borrower and lender *n* on the construction of the syndicate. $Market\ Share_{n,t}$ is the market share of lender *n* as a lead arranger during the twelve months prior to month *t*. We use $Market\ Share_{n,t}$ to proxy for lender *n*'s reputation and market size or power. $Loan\ Facility_k$ is a vector of loan facility fixed effects, which are included to rule out any facility-specific effects, including the effects from the borrower, the lead arranger, the time trend in a particular year, and any loan characteristics. Standard errors are heteroscedasticity robust and clustered at the month level. The regression size is $\sum_{k=1}^{K} M_k \times (100-1)$ observations, where *K* is the total number of syndicated loan facilities in the sample and M_k is the number of lead arrangers in syndicate k. The resulting sample size is nearly 11 million pairs of lenders in unique loan facilities.

The results are reported in Table 3. Six distance measures are shown in Columns (I) to (VI), based on borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. In all regressions, our distance measures show negative coefficients that are significant at the 1% level. That is, the greater the portfolio similarity between a lender and the lead arranger, the greater the likelihood that the lender is chosen as a syndicate member. We also find that a lender's prior relationships with either the lead arranger or the borrower have significantly positive influences on the likelihood of being chosen as a syndicate member. The effect is especially strong for prior lender-borrower relationships, and consistent with the findings in Sufi [35]. Lender *n*'s market share also enhances its likelihood of being included in the syndicate.

Overall, the results suggest that lead arrangers tend to invite lenders that are closer to themselves in terms of asset allocation in their loan portfolios to their syndicates. In other words, the organizational structure of loan syndication increases the degree of interconnectedness of banks over time.

4.2 Determinants of Interconnectedness: Diversification versus Size

To understand the determinants of interconnectedness, we examine the effect of three bank characteristics: (i) market share, (ii) diversification, and (iii) number of specializations. We estimate the following regression:

$$\begin{aligned} Interconnectedness_{i,t} &= \alpha + \beta_1 \cdot Market\ Share_{i,t} + \beta_2 \cdot Diversification_{i,t} \\ &+ \beta_3 \cdot Number\ of\ Specializations_{i,t} + Lead\ Arranger_i' + e_{i,t}, \end{aligned} \tag{10}$$

where the dependent variable $Interconnectedness_{i,t}$ is the level of interconnectedness of bank *i* in month *t*. There are three independent variables in the regression: $Market\ Share_{i,t}$ is bank *i*'s market share in the syndicated loan market as a lead arranger during the twelve months prior to month *t*. We use the dollar volume of loans originated by the lead arranger to construct this variable. Market share is thus a proxy for bank size. $Diversification_{i,t}$ is the diversification measure computed as in equation (4), and $Number\ of\ Specializations_{i,t}$ as a lead arranger. $Number\ of\ Specializations_{i,t}$ varies by the type of specialization. For example, it is the number of 2-digit borrower SIC industries to which the bank lends as a lead arranger if the type of specializations is the 2-digit borrower SIC industry. In addition, $Lead\ Arranger_i$ is a vector of lead arranger (bank) fixed effects. Standard errors are heteroscedasticity robust and clustered at the month level. Note that equation (10) is the general form of the regression, and the inclusion of independent variables and fixed effects varies for different specifications.

The results are reported in Table 4. As discussed in Section 2, interconnectedness can be size- or relationship-weighted and based on six types of specializations. We analyze the determinants for each of the alternative interconnectedness measures. First, we estimate simple regression models of both size- and relationships-weighted interconnectedness on market share, diversification, and the number of specializations individually in Regression (I), (II), and (III) in Panel A. The marginal coefficients on market share, diversification, and number of specializations are all significantly positive at the 1% level, indicating positive association of these variables with interconnectedness. Comparing the R^2 of these regressions helps us assess the explanatory power of these independent variables in interconnectedness. We find that size only explains between 3.5% and 6.7% of the variation in interconnectedness. In contrast, diversification explains more than 80% of the variation in size-weighted interconnectedness and about 50% or more variation in relationship-weighted interconnectedness.[15] In other words, banks with concentrated loan portfolios are less interconnected relative to those with diversified portfolios. Number of specializations explains approximately 20-70% of the variation in interconnectedness. Overall, diversification and number of specialization are relatively more important determinants of loan market interconnectedness than bank size.

In a next step, we include all variables jointly in multivariate regressions and report the results in Panel B of Table 4. We continue to find positive effects of diversification and number of specializations on interconnectedness, significant at the 1% level. An analysis of variance (ANOVA) suggests that lead arranger fixed effects explain more than 60% of the variation in our interconnectedness measures. Including fixed effects thus eliminates a substantial part of the variation. However, even when lead arranger fixed effects are included, the significant, positive

[15] R^2 decreases substantially when we switch from size-weighted to relationship-weighted interconnectedness as diversification is more correlated with size than interbank relationships in the syndicated loan market.

effects of diversification and number of specializations on the interconnectedness measures persist.[16]

4.3 Time Trend in Interconnectedness

Figure 2 plots the monthly time series of the various market-aggregate Interconnectedness Indices from January 1989 to July 2011. Panels A and B show the size- and relationship-weighted Interconnectedness Index based on all six types of specializations, respectively. There was an overall increasing trend in market-aggregate interconnectedness from 1989 until 1995. This was mainly due to the sudden introduction of syndicated lending as a financing vehicle and the subsequent growth in the size and number of participants in the syndicated loan market.

A possible explanation is the benefits to lenders from being able to syndicate large corporate loans. Syndicating, i.e. selling a large proportion of loans that banks originate themselves or participating in loans to borrowers banks usually do not have access to, helps them diversify their loan portfolio. Moreover, the development of the syndicated loan market accommodates the financing needs of large borrowers. Banks face regulatory restrictions such as single counterparty exposure limits as well as regulatory capital requirements that discourages retaining larger exposures to borrowers. The development of the syndicated loan market allows banks to continue lending to, and thus their relationship, with larger firms syndicating a greater fraction of the loan to other banks if exposure limits are binding. Similarly, they are able to reduce capital requirements as syndication removes part of the credit risk associated with the loan from the bank's balance sheet. In order to show that this increasing trend does not dominate our empirical results, we run all regressions excluding data prior to 1995 as a robustness test and find similar results.[17]

Another interesting trend is that interconnectedness dropped significantly during the period from mid-2008 to the end of 2009, i.e. during the crisis period, but it has risen again since the beginning of 2010 and has climbed back to the peak level we observed before the crisis.

Panel C of Figure 2 shows a different perspective regarding the trend in interconnectedness, which is the growth in the relationship-weighted interconnectedness measure relative to the size-

[16] The sign of the coefficients on market share becomes negative in the multivariate regressions, which is due to the multicollinearity among the regressors.
[17] The results based on the post-1995 subsample are available upon request. The tests on *SRISK* and *DIP* are the same based on either the whole sample or the post-1995 subsample as *SRISK* and *DIP* data start from 2000.

weighted interconnectedness measure. Prior to mid-1992, relationship-weighted interconnectedness was slightly below its size-weighted counterpart. Then the two moved almost side by side until mid-1999. Since then relationship-weighted interconnectedness has stayed somewhat higher than size-weighted interconnectedness. Panel C plots interconnectedness based on 4-digit borrower SIC industry while this same trend is observed across all six types of specializations.

5 Interconnectedness and Systemic Risk

A higher interconnectedness measure suggests that a bank is more vulnerable to systemic shocks. Moreover, asset-side interconnected banks are more vulnerable because externalities of liability-side interconnectedness arise when short-term fund providers withdraw funds from these institutions.

In this section, we empirically examine the relationship between our measure of interconnectedness and the various systemic risk measures discussed earlier. We first examine at the bank level the relationship between interconnectedness and systemic risk measured by *SRISK*, *CoVaR*, and *DIP*. Then we explore at the market level how changes of aggregate interconnectedness affects aggregate systemic risk measured by *CATFIN*.

5.1 Bank-level (Cross-sectional) Tests

Banks become interconnected as they invest in similar loan portfolios through loan syndication. In fact, this behavior reduces each bank's individual default risk via diversification of loan exposures and thus is beneficial from a microprudential perspective (Simons [33]). However, the interconnectedness creates systemic risk because not only are banks vulnerable to common shocks due to exposure to similar assets, but also problems of some banks can spread throughout the syndicate network to other banks, for example, funding shocks or adverse asset price movements due to an increase in correlations among assets. Consequently, when a financial crisis occurs, interconnectedness will magnify the severity and consequences of the crisis (Bernanke [10]). We examine first whether more heavily interconnected banks in the syndicated loan market are greater contributors to systemic risk and then, second, whether this effect is amplified during recessions.

We first match *SRISK*, *CoVaR*, and *DIP* as systemic risk measures with the time-series of our interconnectedness measure at the bank level. Figure 3 shows graphically the association between interconnectedness and systemic risk during the most recent recession period from December 2007 to June 2009. As an example, we plot a bank's *SRISK%*, 5% *CoVaR*, and *DIP* averaged for this period against its relationship-weighted, 4-digit borrower SIC industry-based interconnectedness measures also averaged for the period in Panels A, B, and C of Figure 3, respectively. We observe a positive relationship between interconnectedness and all three systemic risk measures. That is, the more interconnected banks contribute more to systemic risk. This relationship holds for both size- and relationship-weighted interconnectedness as well as across all six types of specializations.

To more formally test this relationship, we first regress each of the three systemic risk measures on interconnectedness alone to examine the simple correlation between the two and then add control variables in a multiple regression setting as a second step. The general form of the regression we estimate is as follows:

$$
\begin{aligned}
&System\ Risk_{i,t} = \alpha + \beta_1 \cdot Interconnectedness_{i,t} \\
&+\beta_2 \cdot \left(Interconnectedness_{i,t} \times Recession_t\right) + \beta_3 \cdot European_i \\
&+\beta_4 \cdot \left(Interconnectedness_{i,t} \times European_i\right) + \beta_5 \cdot ln\left[Market\ Value_{i,t}\right] \\
&+\beta_6 \cdot Market\ Share_{i,t} + Lead\ Arranger_i' + e_{i,t}.
\end{aligned}
\tag{11}
$$

The dependent variable is $System\ Risk_{i,t}$, the systemic risk measure of bank *i* in month *t*. It can be either *SRISK*, *CoVaR*, or *DIP*. The key independent variable $Interconnectedness_{i,t}$ is the level of interconnectedness of bank *i* in month *t*. $Recession_t$ is an indicator variable equal to 1 if month *t* falls into recessions as identified by the NBER.[18] $European_i$ is an indicator variable equal to 1 if bank *i* is headquartered in Europe. We are also interested in how interconnectedness may play a different role during recessions and in Europe. Thus, two interaction terms are included in the regression: $\left(Interconnectedness_{i,t} \times Recession_t\right)$ and $\left(Interconnectedness_{i,t} \times European_i\right)$. In order to control for bank size, we include the following two control variables:

[18] The NBER identifies three recession periods during our sample period: July 1990 – March 1991, March 2001 – November 2001, and December 2007 – June 2009.

$ln[Market\ Value_{i,t}]$ is the natural logarithm of bank *i*'s market value of equity in month *t*, and $Market\ Share_{i,t}$ is its market share in the syndicated loan market as a lead arranger during the twelve months prior to month *t*. $Lead\ Arranger_i$ is a vector of lead arranger (bank) fixed effects. Standard errors are heteroscedasticity robust and clustered at the month level.

Table 5 shows the results from the simple regressions of various systemic risk measures on interconnectedness. The coefficients on both size- and relationship-weighted interconnectedness across all six types of specializations are significantly positive at the 1% level, indicating that there is positive association between interconnectedness and systemic risk. Based on R^2, such association is the strongest with *CoVaR* (23-32%), followed by *SRISK* (2-7%) and *DIP* (1-3%).

5.1.1 Interconnectedness and *SRISK*

Table 6 reports the multiple regression results for SRISK. Regression (I) does not include lead arranger fixed effects, whereas Regression (II) does. In the absence of lead arranger fixed effects [Regression (I)], we see consistently positive and statistically significant coefficients on size- and relationship-weighted interconnectedness as well as on the interaction term of interconnectedness and recession across all six types of specializations. That is, interconnectedness contributes positively to *SRISK* and this contribution becomes stronger during recessions. Interestingly, European banks present a higher level of *SRISK* in general, and the effect of interconnectedness on *SRISK* is also stronger among European banks than U.S. banks. The coefficients on the natural logarithm of the market value of equity and market share as a lead arranger are significantly positive indicating that larger banks carry higher (absolute) systemic risk.

When we include lead arranger fixed effects in the model [Regression (II)], the coefficients on interconnectedness become weaker, and some are no longer significant. Nonetheless, the coefficients on the interaction term of interconnectedness and recession remain consistently positive and significant, consistent with interconnectedness having an amplifying effect on systemic risk during recessions. With lead arranger fixed effects, we can no longer estimate the difference between European and U.S. banks in *SRISK*. However, the significantly positive coefficients on the interaction term of interconnectedness and European banks still suggest that interconnectedness has a stronger effect on European than US banks.[19]

SRISK is composed of two key factors: (i) the long-run marginal expected shortfall (*LRMES*) of the bank and (ii) its leverage. In order to understand which component(s) of *SRISK* interconnectedness contributes most, we regress the natural logarithm of *LRMES* and the quasi-market leverage independently on interconnectedness using the same specification as in (11) with lead arranger fixed effects. The results with *LRMES* as the dependent variable are shown in Panel A of Table 7, and those with leverage are in Panel B.

We find that interconnectedness increases as a bank's *LRMES* increases, which is consistent with interconnected banks having larger downside risk if there is an overall market downturn. Moreover, we find that interconnectedness also increases as the market leverage of the respective bank increases.

5.1.2 Interconnectedness and *CoVaR*

Table 8 reports results from regressing the natural logarithm of 5% *CoVaR* on interconnectedness, the interaction term of interconnectedness and recession, the natural logarithm of the market value of equity, and the market share as a lead arranger. We use the same specifications as for *SRISK* in Tables 6 and 7.[20] As in Table 6, Regression (I) does not include lead arranger fixed effects, whereas Regression (II) includes fixed effects.

The coefficients on interconnectedness are mostly insignificant in Regression (I), and more than half of them are significantly negative in Regression (II) when lead arranger fixed effects are added. This indicates that in spite of the apparently positive relationship between interconnectedness and *CoVaR* as reported in Panel B of Table 5, interconnectedness does not directly contribute to *CoVaR* under normal economic conditions.

However, the coefficients on the interaction term of interconnectedness and recession are significantly positive at the 1% level in all specifications, i.e. there is a positive incremental effect of interconnectedness on *CoVaR* during recessions. In Regression (I), this incremental effect is

[19] The coefficients on the market value of bank equity turn significantly negative, which is related to the absorption of the size effect partially by lead arranger fixed effects.
[20] We do not include control variables relating to whether a bank is headquartered in Europe or the U.S. because CoVaR covers U.S. banks only.

large enough to make the total effect of interconnectedness on *CoVaR* (the coefficient on interconnectedness plus the coefficient on the interaction term) significantly positive during recessions. In Regression (II) with lead arranger fixed effects, the incremental effect of interconnectedness during recessions approximately offsets the negative effect observed in normal times.

5.1.3 Interconnectedness and *DIP*

Similar to Table 8, Table 9 reports coefficient estimates from regressing the natural logarithm of the monthly *DIP* in euros on the same set of independent variables including interconnectedness, the interaction term of interconnectedness and recession, the natural logarithm of the market value of equity, and the market share as a lead arranger. Note that the number of observations drops compared to that in the *SRISK* regressions (Tables 6 and 7) as the *DIP* measure is only available for European banks. Again, Regression (I) does not include lead arranger fixed effects, whereas Regression (II) includes fixed effects.

Regardless whether the fixed effects are included or not, the coefficients on interconnectedness are all negative, and about half of them are significant at the 1% or 5% level. That is, under normal economic conditions, interconnectedness reduces *DIP*, the distress insurance premium for European banks. As discussed earlier, there are substantial benefits to syndication as discussed in Section 4 above, but it simultaneously creates the potential for systemic risk. Thus in normal times, the benefits of syndicated lending may exceed the cost arising from systemic risk.

Nonetheless, interconnectedness works in just the opposite way on *DIP* during NBER recession periods as the coefficients on the interaction term of interconnectedness and recession are all significantly positive at the 1% level. Importantly, the magnitude of the coefficients suggests that the "costs" arising from systemic risk offset the "benefits" of syndication during recessions.

5.2 Market-level (Time-series) Tests

SRISK, *CoVaR*, and *DIP* provide systemic risk measures for each bank individually and thus assess the cross-sectional differences in the contribution of banks to systemic risk. We can also ask whether more interconnectedness in the overall banking sector increases systemic risk over time.

To assess this, we use an aggregate systemic risk measure, called *CATFIN*, which has been shown to forecast recessions that arise from the excessive risk-taking of the US banking sector using different *VaR* measures (Allen et al. [6]).

We estimate the following time-series regression:

$$
\begin{aligned}
CATFIN_t &= \alpha + \beta_1 \cdot Interconnectedness\ Index_t \\
&+\beta_2 \cdot (Interconnectedness\ Index_t \times Recession_t) \\
&+\beta_3 \cdot ln[Market\ Size_t] + \beta_4 \cdot Herfindahl_t + e_t,
\end{aligned}
\tag{12}
$$

where the dependent variable $CATFIN_t$ is the monthly time series of *CATFIN*. The key independent variables include (i) the $Interconnectedness\ Index_t$, the monthly market-aggregate Interconnectedness Index, and (ii) $(Interconnectedness\ Index_t \times Recession_t)$, the interaction term of Interconnectedness Index and recession. We include two other variables to control for market characteristics: $ln[Market\ Size_t]$ is the natural logarithm of the size of the U.S. syndicated loan market measured by the total amount of loans, and $Herfindahl_t$ is the Herfindahl index of the market. Standard errors are heteroscedasticity robust.

The results are reported in Table 10. Regression (I) includes only the market-aggregate Interconnectedness Index and its interaction with recession as independent variables. Regression (II) puts in size and the Herfindahl index of the market as additional controls.

Our time-series tests are very similar and sometimes even stronger compared to the cross-sectional results obtained earlier. In all specifications, we find significantly negative coefficients on the Interconnectedness Index and significantly positive coefficients on its interaction with recession, all at the 1% level. In periods of economic upswings, a more interconnected banking system as a result of loan syndications benefits from the diversification of its banks. However, interconnectedness imposes significant systemic costs during recessions.

6 Conclusion

This paper studies interconnectedness of banks in the syndicated loan market as a major source of systemic risk. Using a dataset of newly originated syndicated loans during the period from January

1988 to July 2011, we develop a set of novel measures to describe how banks are interconnected based on the similarity of their loan portfolios and analyze bank behavior and participation in the U.S. syndicated loan market.

We find a propensity of banks to concentrate syndicate lenders rather than to diversify them. That is, banks are more likely to collaborate in loan syndicates the more similar they are with respect to their loan portfolios. This is an important finding as it provides novel evidence for a trade-off that has been recognized in the theoretical literature: Banks diversify (in our case, getting other banks to participate in the loans they arrange), but at the same time, reduce the diversity of the financial sector because banks become more similar to one another.

In the next step, we relate interconnectedness in the loan market to various measures of systemic risk. We use both cross-sectional measures to assess variations in the contribution of banks to the systemic risk of the financial sector and a time-series measure to exploit the effect of interconnectedness on the U.S. financial system over time. We find that interconnectedness of banks can explain the downside exposure of these banks to systemic shocks.

Our results have important policy implications. The Bank of International Settlement (BIS) published an updated methodology to identify G-SIFIs in July 2013 (BIS, 2013). The indicators to identify G-SIFIs comprise five factors: (1) bank size, (2) interconnectedness, (3) substitutability of services, (4) complexity, and (5) cross-border activity each with an equal weight. While these factors include interconnectedness, its level is determined based on intra-financial system assets and liabilities, that is, direct exposures among financial institutions. We propose interconnectedness through large corporate loans as a 6th indicator that helps to identify G-SIFIS and to calibrate appropriate capital surcharges for these institutions.

Similarly, the Financial Stability Oversight Council (FSOC), which was created in the U.S. following the Dodd-Frank Wall Street Reform after the 2008-2009 financial crisis, has the mandate to monitor and address the overall risks to financial stability. It has the authority to make recommendations as to stricter regulatory standards for the largest and most interconnected institutions to their primary regulators. We propose a new method based on interconnectedness through large corporate loans as part of FSOC's systemic risk oversight and monitoring system.

Acknowledgement: We thank Robert Engle and NYU's V-Lab for providing the *SRISK* measures, Tobias Adrian for the *CoVaR* measures, Lamont Black for the *DIP* measure, and Yi Tang for the *CATFIN* measure. We further thank Viral Acharya, Arnoud Boot, Rob Capellini, Hans Degryse (discussant), Markus Fischer, Agnese Leonello (Discussant), Steven Ongena, Anjan Thakor, Neeltje van Horen (discussant), and seminar participants at University of Muenster, University of Frankfurt, the 2012 AEA Annual Meeting, the 2012 EFA Annual Meeting, the CESifo "The Banking Sector and The State" Conference, and the 6th Swiss Winter Finance Conference on Financial Intermediation for their helpful suggestions and comments.

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Appendix 1: Variable Definitions

This appendix lists the variables used in the empirical analysis and their definitions.

Variable	Definition
Borrower Relationship	An indicator variable for whether a potential lender has previous relationships with the borrower
CATFIN	Aggregate systemic risk of the financial sector
Recession	An indicator variable for whether a month falls into recession periods identified by the NBER
CoVaR	1% or 5% contagion value-at-risk of a U.S. bank measured in U.S. dollars or percentage
DIP	Distressed insurance premium of a European bank in billions of euros
Distance	Distance between two banks based on their syndicated loan portfolios as lead arrangers during the previous twelve months
Diversification	Diversification of a bank based on its syndicate loan portfolio
European	An indicator variable for whether the bank is headquartered in Europe
Herfindahl	The Herfindahl index of the U.S. syndicated loan market
Interconnectedness	Interconnectedness of a bank
Interconnectedness Index	Market-aggregate interconnectedness
Lead Arranger	Lead arranger (bank) fixed effect
Lead Relationship	An indicator variable for whether a potential lender has previous relationships with the lead arranger
LRMES	Long-run marginal expected shortfall of a bank in percentage
Leverage	Quasi-market leverage of a bank in percentage
Loan Facility	Loan facility fixed effect

Appendix 1 (continued)

Variable	Definition
Market Share	Market share of a bank in the U.S. syndicated loan market as a lead arranger
Market Size	The size of the U.S. syndicated loan market measured by the total amount of loans
Market Value	Market value of a bank's equity in U.S. dollars
Number of Specializations	Number of specializations a bank is engaged in as a lead arranger
SRISK	Systemic capital shortfall of a bank in U.S. dollars
SRISK%	Relative capital shortfall of a bank as a percentage of total systemic risk of the market
Systemic Risk	Any systemic risk measure
Syndicate Member	An indicator variable for whether a potential lender is chosen by the lead arranger to be a loan syndicate member

Appendix 2: Examples of Computing Distance between Lead Arrangers

This appendix shows how distance is computed by examples. Distance between two lead arrangers is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specialization in this appendix is based on borrower SIC industry division. We show below the computation of such distance among JPMorgan Chase (JPM), Bank of America (BAC), and Citigroup (C), which were the top three lead arrangers as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months. Note that distance is the key component for computing interconnectedness – the smaller the distance between two lead arrangers, the more interconnected they are.

SIC Industry Division (2-digit SIC Industries)	JPM (1st)	BAC (2nd)	C (3rd)	$(JPM-BAC)^2$	$(JPM-C)^2$	$(BAC-C)^2$
Agriculture, Forestry & Fishing (01-09)	0.0288%	0.1695%	0.0000%	0.00000198	0.00000008	0.00000287
Mining (10-14)	5.0995%	3.7503%	4.7749%	0.00018203	0.00001054	0.00010498
Construction (15-17)	2.3374%	6.3482%	0.3057%	0.00160872	0.00041276	0.00365120
Manufacturing (20-39)	28.6855%	23.3487%	35.3001%	0.00284810	0.00437536	0.01428362
Transportation, Communications, Electric, Gas & Sanitary Services (40-49)	12.2990%	12.0246%	20.1229%	0.00000753	0.00612126	0.00655812
Wholesale Trade (50-51)	2.4575%	3.8202%	0.9026%	0.00018570	0.00024177	0.00085124
Retail Trade (52-59)	6.8148%	7.3637%	2.8273%	0.00003013	0.00159001	0.00205790
Finance, Insurance & Real Estate (60-67)	29.1845%	30.7133%	18.4803%	0.00023371	0.01145801	0.01496453
Services (70-89)	13.0931%	12.4389%	17.1766%	0.00004280	0.00166749	0.00224458
Public Administration (91-97)	0.0000%	0.0226%	0.1096%	0.00000005	0.00000120	0.00000076
Total	100%	100%	100%	0.00514075	0.02587847	0.04471981
			Distance:	0.07169901	0.16086787	0.21147059

Appendix 3: Distance among Top Ten Lead Arrangers

This appendix shows distance between any two top ten lead arrangers as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months. Distance between two lead arrangers is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specialization in this appendix is based on borrower SIC industry division. The top ten lead arrangers as of January 2007 were: JPMorgan Chase (JPM), Bank of America (BAC), Citigroup (C), Wachovia Bank (WB), Credit Suisse (CSGN), Deutsche Bank (DB), Royal Bank of Scotland (RBS), Goldman Sachs (GS), Barclays (BARC), and UBS (UBSN). Note that distance is the key component for computing interconnectedness – the smaller the distance between two lead arrangers, the more interconnected they are.

	JPM	BAC	C	WB	CSGN	DB	RBS	GS	BARC	UBSN
JPM	-									
BAC	0.0717	-								
C	0.1609	0.2115	-							
WB	0.2296	0.2102	0.2358	-						
CSGN	0.3351	0.3539	0.2805	0.3200	-					
DB	0.1739	0.1884	0.1352	0.1748	0.2834	-				
RBS	0.3021	0.3398	0.1875	0.2907	0.2983	0.2020	-			
GS	0.2515	0.2786	0.1347	0.1859	0.2587	0.1618	0.1808	-		
BARC	0.4385	0.4464	0.3492	0.2830	0.4334	0.3584	0.3752	0.2364	-	
UBSN	0.4058	0.4196	0.3909	0.4069	0.1685	0.4063	0.4284	0.3722	0.5222	-

Appendix 4: Lead Arrangers with Systemic Risk Measures

This appendix lists lead arrangers in the U.S. syndicated loan market for which various systemic risk measures are available. There are 62 lead arrangers with *SRISK* measures (Panel A), 44 with *CoVar* measures (Panel B), and 22 with *DIP* measures (Panel C).

A. Lead Arrangers with *SRISK* Measures

	Financial Institution	Ticker		Financial Institution	Ticker
1	Allied Irish Banks	ALBK	32	Keycorp	KEY
2	American Express	AXP	33	Lehman Brothers	LEH
3	Banco Bilbao Vizcaya Argentari	BBVA	34	Lloyds Banking Group	LLOY
4	Bank of China	F3988	35	Marshall & Ilsley	MI
5	Bank of America	BAC	36	Mediobanca	MB
6	Bank of Ireland	BKIR	37	Merrill Lynch	MER
7	Bank of Montreal	BMO	38	Mizuho Financial Group	F8411
8	Bank of New York Mellon	BK	39	Morgan Stanley	MS
9	Bank of Tokyo-Mitsubishi UFJ	F8306	40	National Bank of Canada	NA
10	Barclays	BARC	41	National City Corporation	NCC
11	BB&T Corporation	BBT	42	Natixis	KN
12	Bear Stearns	BSC	43	Nomura	F8604
13	BNP Paribas	BNP	44	Nordea Bank	NDA
14	Capital One Financial	COF	45	Northern Trust	NTRS
15	CIT Group	CIT	46	PNC Financial Services	PNC
16	Citigroup	C	47	Prudential	PRU
17	Comerica	CMA	48	Regions Financial Corp	RF
18	Commerzbank	CBK	49	Royal Bank of Canada	RY
19	Compass Bank	CBSS	50	Royal Bank of Scotland	RBS
20	Credit Agricole SA	ACA	51	Skandinaviska Enskilda Banken	SEBA
21	Credit Suisse	CSGN	52	Societe Generale	GLE
22	Crédit Lyonnais	FLY	53	State Street	STT
23	Danske Bank	DANSKE	54	Suntrust Banks	STI
24	Deutsche Bank	DBK	55	Toronto-Dominion Bank	TD
25	Fifth Third Bancorp	FITB	56	UBS	UBSN
26	Goldman Sachs	GS	57	UniCredit SpA	UCG
27	HSBC	HSBA	58	US Bancorp	USB
28	Huntington Bancshares	HBAN	59	Wachovia Bank	WB
29	ING Group	INGA	60	Washington Mutual	WM
30	Intesa Sanpaolo SpA	ISP	61	Wells Fargo	WFC
31	JPMorgan Chase	JPM	62	Zions Bancorporation	ZION

Appendix 4 (continued)

B. Lead Arrangers with *CoVaR* Measures

	Financial Institution	Ticker		Financial Institution	Ticker
1	American Express	AXP	23	Jefferies Finance LLC	JEF
2	Ares Capital Corp	ARCC	24	JPMorgan Chase	JPM
3	Bank of Hawaii	BOH	25	Keycorp	KEY
4	Bank of America	BAC	26	Lloyds Banking Group	MI
5	Bank of New York Mellon	BK	27	Mercantile Bank	MBWM
6	BB&T Corporation	BBT	28	Morgan Stanley	MS
7	Capital One Financial	COF	29	Northern Trust	NTRS
8	Charter One Bank	CF.6	30	Paine Webber	PWJ.
9	Chemical Banking Corp	CHFC	31	PNC Financial Services	PNC
10	CIT Group	CIT	32	PrivateBancorp Inc	PVTB
11	Citigroup	C	33	Prudential	PRU
12	City National Bank	CYN	34	Regions Financial Corp	RF
13	Comerica	CMA	35	State Street	STT
14	Cullen/Frost Bankers	CFR	36	Suntrust Banks	STI
15	Eaton Vance	EV	37	TrustCo Bank Corp	TRST
16	Fifth Third Bancorp	FITB	38	UMB Financial Corp	UMBF
17	FINOVA Capital Corp	3FNVG	39	US Bancorp	USB
18	First Commonwealth Bank	FCF	40	Valley National Bank	VLY
19	First Horizon National Corp	FHN	41	Wells Fargo	WFC
20	Goldman Sachs	GS	42	Whitney National Bank	WTNY
21	Guaranty Bank	GBNK	43	Wilmington Trust Corp	WL
22	Huntington Bancshares	HBAN	44	Zions Bancorporation	ZION

Appendix 4 (continued)

C. Lead Arrangers with *DIP* Measures

	Financial Institution	Ticker		Financial Institution	Ticker
1	Allied Irish Banks	ALBK	12	ING Group	INGA
2	Banco Bilbao Vizcaya Argentari	BBVA	13	Intesa Sanpaolo SpA	ISP
3	Bank of Ireland	BKIR	14	Lloyds Banking Group	LLOY
4	Barclays	BARC	15	Mediobanca	MB
5	BNP Paribas	BNP	16	Natixis	KN
6	Commerzbank	CBK	17	Nordea Bank	NDA
7	Credit Agricole SA	ACA	18	Royal Bank of Scotland	RBS
8	Credit Suisse	CSGN	19	Skandinaviska Enskilda Banken	SEBA
9	Danske Bank	DANSKE	20	Societe Generale	GLE
10	Deutsche Bank	DBK	21	UBS	UBSN
11	HSBC	HSBA	22	UniCredit SpA	UCG

Figure 1: The U.S. Syndicated Loan Market, 1988-2011

This figure shows the size of the U.S. syndicated loan market by year from 1988 to 2011. Market size is measured by the total newly originated syndicated loan amount during the year in billions of U.S. dollars. Note that data for the year of 2011 are only available through July of that year.

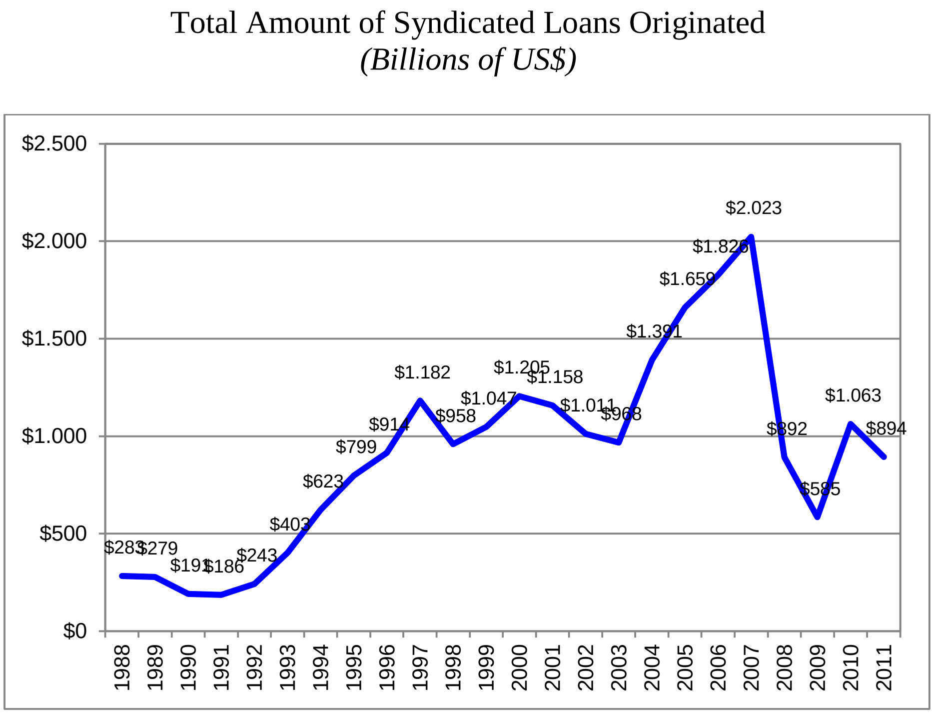

Figure 2: Time Series of Interconnectedness

This figure shows the time series of the monthly Interconnectedness Index, aggregated at the market level. Interconnectedness among lead arrangers is computed based on their distance in specializations in the U.S. syndicated loan market. Lender specializations are examined in borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. Panel A plots the market-aggregate, size-weighted interconnectedness from January 1989 to July 2011, whereas Panel B plots the market-aggregate, relationship-weighted interconnectedness. Panel C compares the market-aggregate, size-weighted interconnectedness to its relationship-weighted counterpart over time based on 4-digit borrower SIC industry.

A. Size-weighted Interconnectedness Index

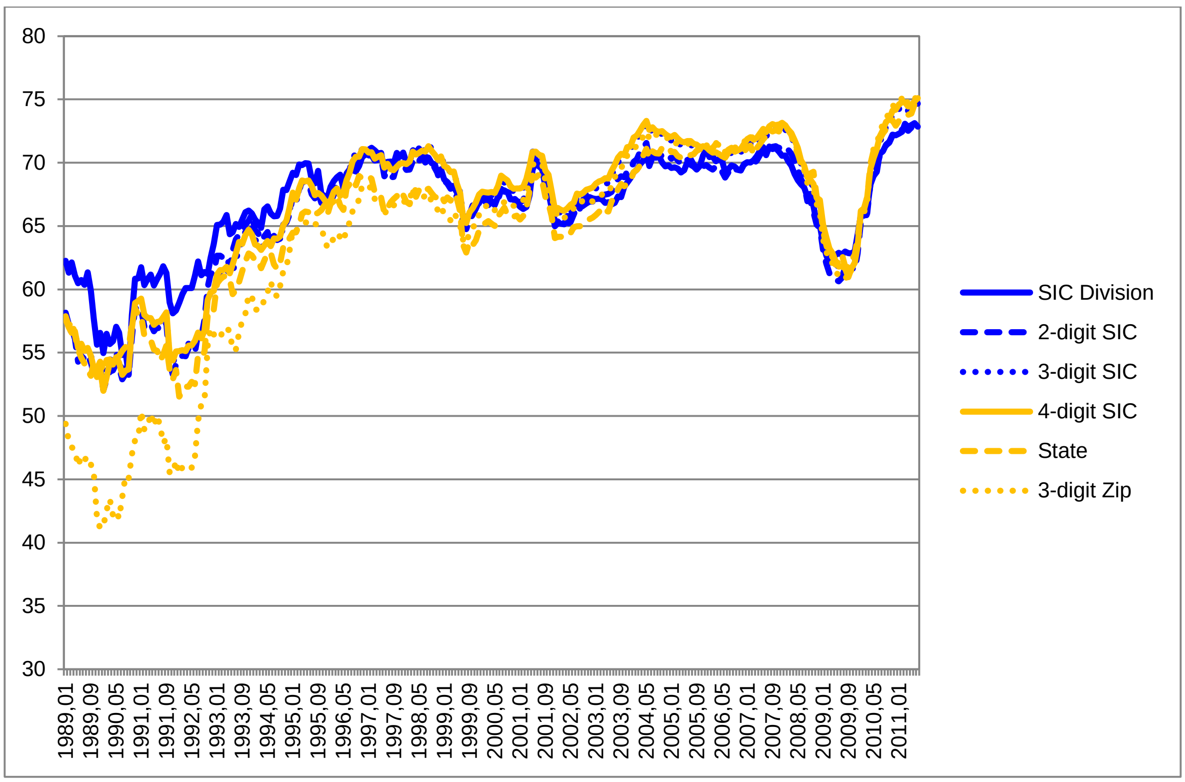

Figure 2 (continued)

B. Relationship-weighted Interconnectedness Index

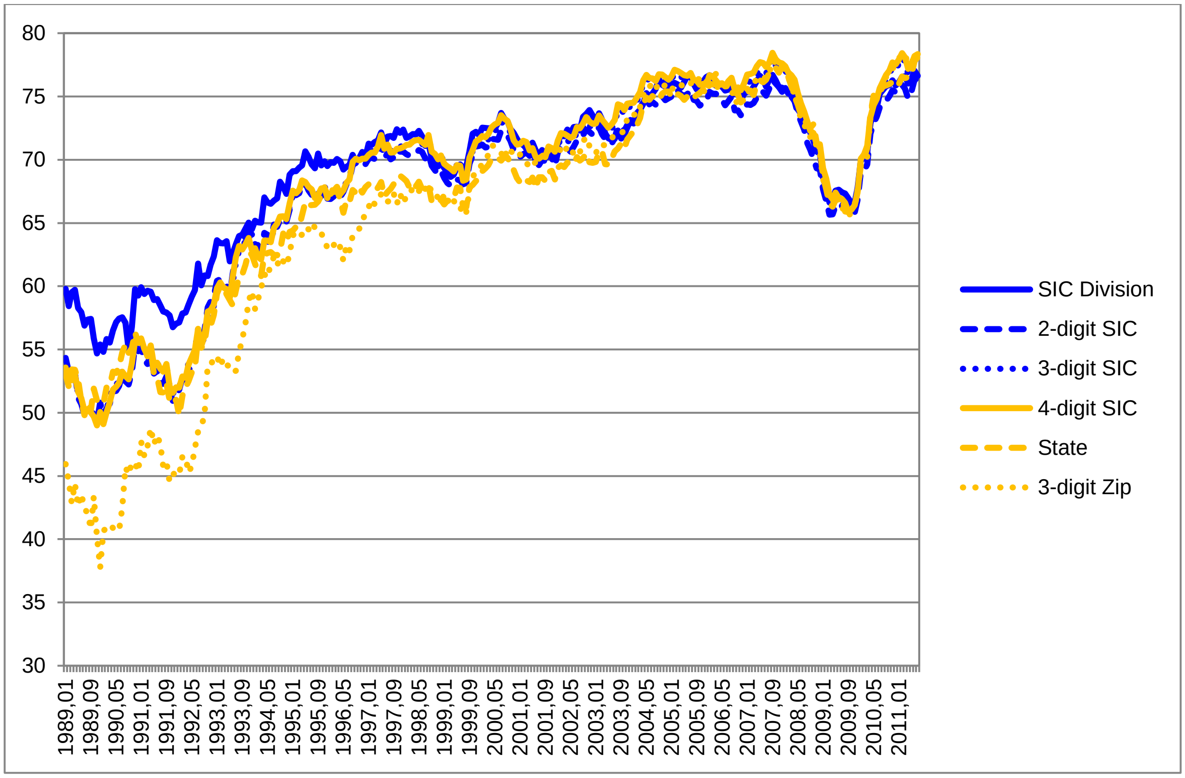

Figure 2 (continued)

C. Size- vs. Relationship-weighted Interconnectedness Index based on 4-digit borrower SIC Industry

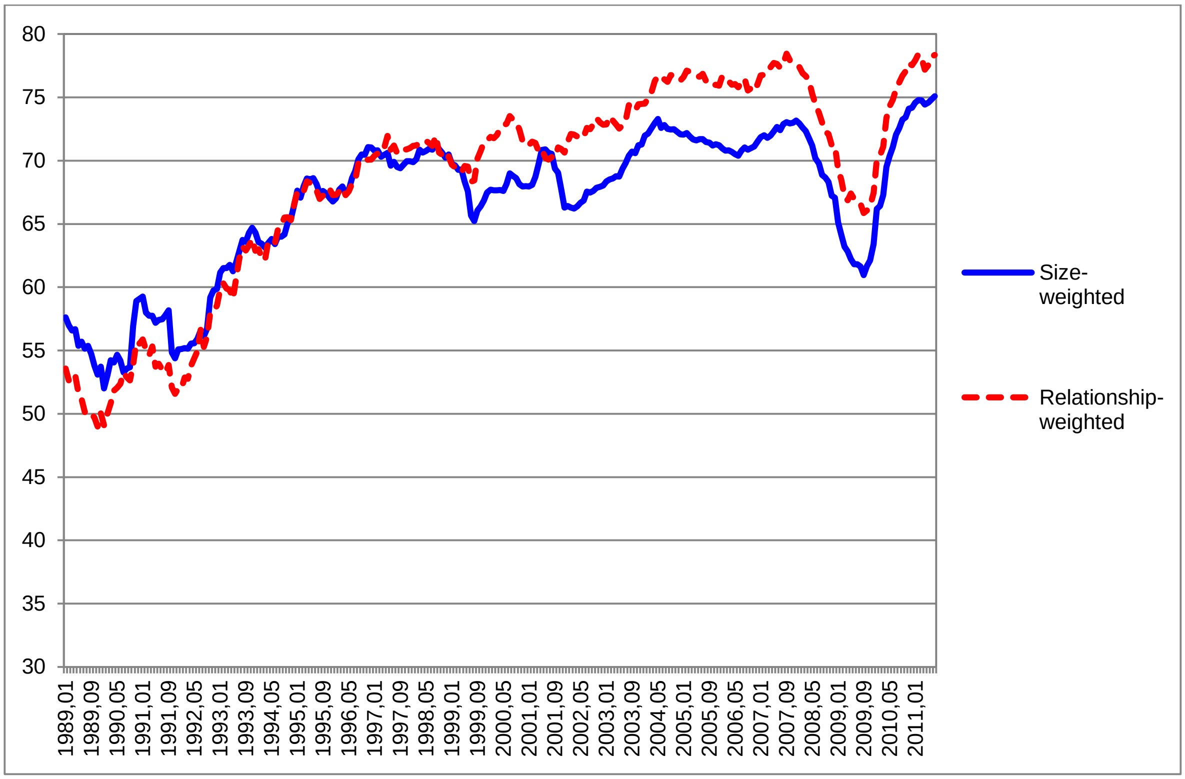

Figure 3: Interconnectedness and Systemic Risk

This figure shows the association between interconnectedness and systemic risk among lead arrangers in the U.S. syndicated loan market during the most recent recession from December 2007 to June 2009. Interconnectedness of a lead arranger is relationship-weighted and based on 4-digit borrower SIC industry in this appendix. Systemic risk is measured by *SRISK*, *CoVaR*, and *DIP*, and is plotted against interconnectedness in Panels A, B, and C, respectively. Interconnectedness and systemic risk measures are all averaged during the recession period.

A. Interconnectedness and *SRISK*

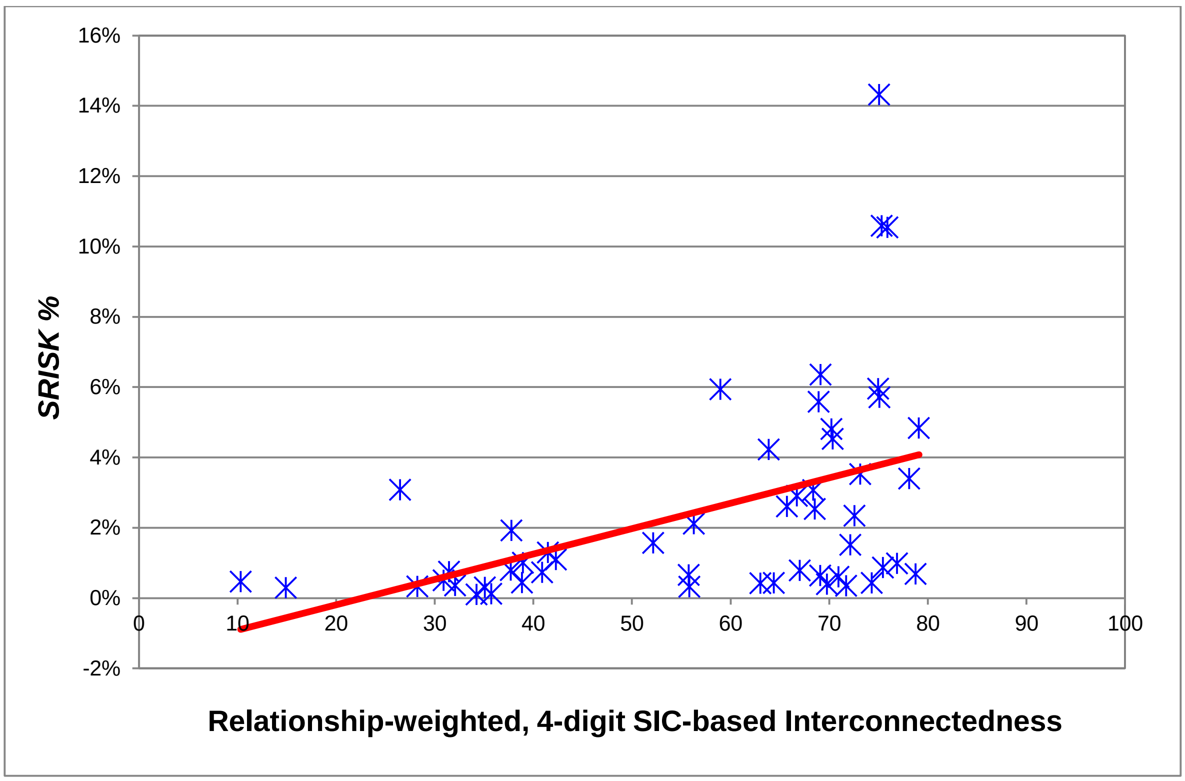

Figure 3 (continued)

B. Interconnectedness and *CoVaR*

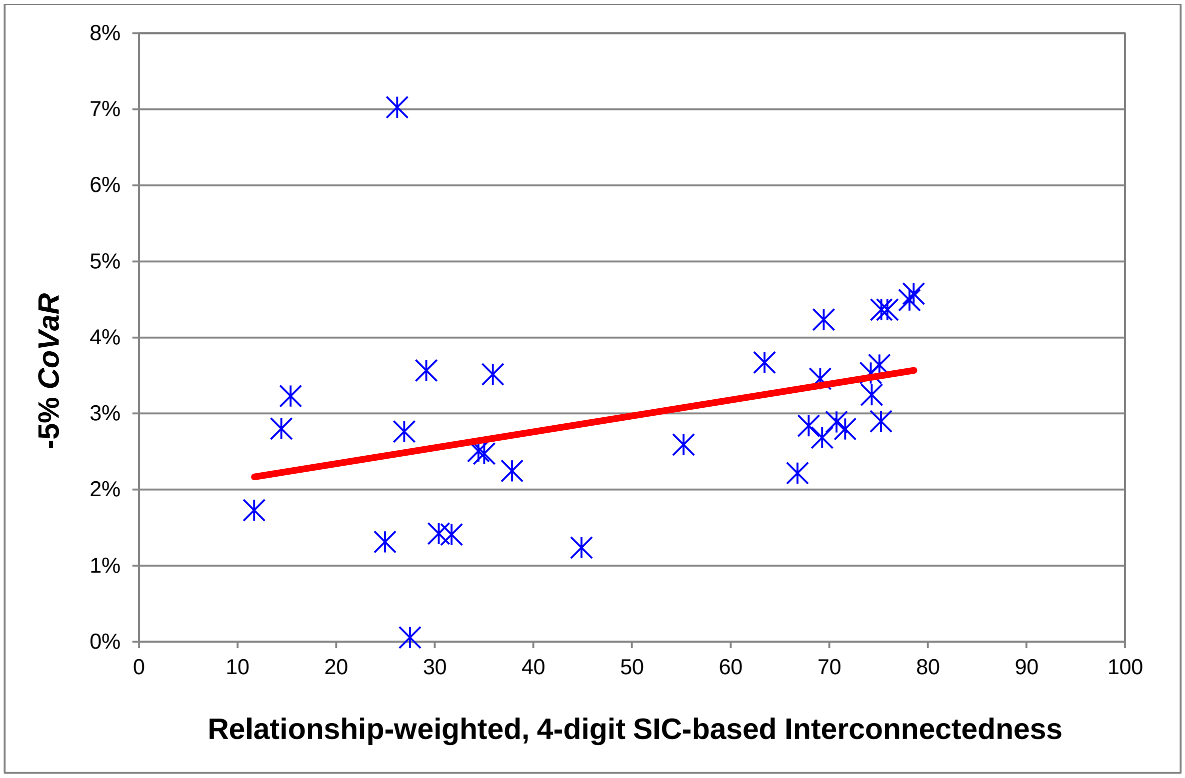

Figure 3 (continued)

C. Interconnectedness and *DIP*

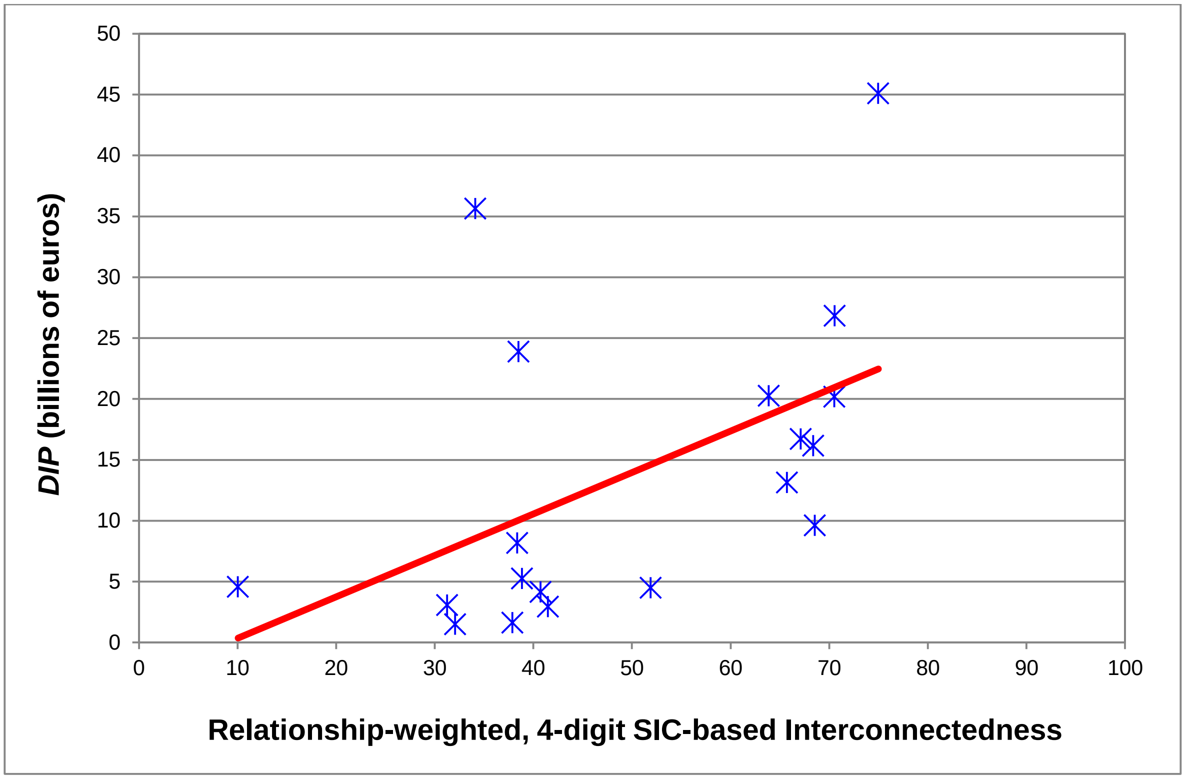

Table 1: Summary Statistics for Syndicated Loan Facilities

This table presents summary statistics for the sample of syndicated loan facilities made to U.S. firms between January 1988 and July 2011. Lead arrangers are ranked by total loan facility amount originated, and loan amount is split equally over all lead arrangers for loans with multiple leads. Panel A reports lead arranger characteristics based on 37,311 unique lead arranger-months. Panels B and C report borrower and loan characteristics, respectively, based on 91,715 loan facilities.

A. Lead Arranger Characteristics
(Based on 37,311 lead arranger-months)

Based on previous 12 months:	*N* =	Mean	*SD*	10^{th}	50^{th}	90^{th}
Market share (%)	37,311	0.73	2.78	0.00	0.03	1.16
# of loans as lead arranger	37,311	35	112	1	4	83
$ of loans as lead arranger ($mm)	37,311	6,670	30,900	16	230	10,400

B. Borrower Characteristics
(Based on 91,715 loan facilities)

	N =	Mean	*SD*	10^{th}	50^{th}	90^{th}
All borrowers:						
Sales at closing ($mm)	59,877	2,800	12,400	52	411	5,580
# of previous syndicated loans	91,715	2.38	4.24	0	1	6
Private firm indicator	72,633	0.37	0.48	0	0	1
Public, unrated firm indicator	72,633	0.28	0.45	0	0	1
Public, rated firm indicator	72,633	0.34	0.47	0	0	1
Borrowers with *Compustat* data:						
Total book assets ($mm)	40,414	11,000	68,875	89	893	14,381
Book leverage ratio	40,243	0.37	0.28	0.05	0.34	0.69
Earnings to asset ratio	38,211	0.06	0.26	-0.02	0.07	0.16
S&P debt rating indicator	42,009	0.49	0.50	0	0	1
S&P investment-grade indicator	20,417	0.55	0.50	0	1	1

Table 1 (continued)

C. Loan Characteristics
(Based on 91,715 loan facilities)

	N =	Mean	SD	10^{th}	50^{th}	90^{th}
Syndicated loan terms:						
Facility amount ($mm)	91,715	236	599	12.5	80	500
Maturity (months)	81,384	48	50	12	48	82
Spread on drawn funds (bps)	76,169	233	154	50	225	400
Term loan indicator	91,715	0.32	0.46	0	0	1
Syndicated structure:						
# of lenders in the syndicate	76,799	6.93	7.22	2	4	15
# of lead arrangers in the syndicate	91,715	1.24	0.63	1	1	2
% retained by lead arranger(s)	19,738	36.04	25.27	9.78	29.41	70.76
Purpose of loan indicators:						
Working capital/corporate	91,715	0.62	0.48	0	1	1
Refinancing	91,715	0.22	0.41	0	0	1
Acquisitions	91,715	0.23	0.42	0	0	1
Backup lines	91,715	0.07	0.25	0	0	0

Table 2: Summary Statistics of Distance, Interconnectedness, and Systematic Risk Measures

This table reports summary statistics of various distance, interconnectedness, and systemic risk measures. Distance between two lead arrangers is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Interconnectedness of a lead arrangers can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations. Rows (I)-(VI) in Panels A and B represent distance and interconnectedness with regard to lender specializations in borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. Panel A summarizes the distance measures of 5,223,284 lead arranger pair-months. Panel B shows summary statistics of the interconnectedness measures of 37,311 lead arranger-months. Systemic risk of a lead arranger is measured by *SRISK*, *CoVaR*, and *DIP*. Panel C reports the *SRISK* measures of 5,799 lead arranger-months, the *CoVaR* measures of 1,767 lead arranger-quarters, and the *DIP* measure of 1,414 lead arranger-months.

A. Distance Measures

	N =	Mean	*SD*	10^{th}	50^{th}	90^{th}
(I) Distance in borrower SIC division	5,216,624	0.912	0.385	0.378	0.975	1.414
(II) Distance in 2-digit borrower SIC	5,216,624	1.007	0.317	0.531	1.050	1.414
(III) Distance in 3-digit borrower SIC	5,216,624	1.009	0.310	0.540	1.049	1.414
(IV) Distance in 4-digit borrower SIC	5,216,624	1.009	0.309	0.539	1.049	1.414
(V) Distance in borrower state	5,215,278	1.006	0.327	0.513	1.056	1.414
(VI) Distance in 3-digit borrower ZIP	5,090,280	0.974	0.317	0.490	1.018	1.414

B. Interconnectedness Measures

	N =	Mean	*SD*	10^{th}	50^{th}	90^{th}
Size-weighted interconnectedness:						
(I) based on borrower SIC division	37,311	50.2	17.6	25.5	49.2	74.5
(II) based on 2-digit borrower SIC	37,311	46.9	19.1	26.1	44.6	75.2
(III) based on 3-digit borrower SIC	37,311	47.3	19.8	26.4	45.3	76.2
(IV) based on 4-digit borrower SIC	37,311	47.5	20.0	26.3	45.4	76.3
(V) based on borrower state	37,311	46.7	19.0	25.4	43.6	74.6
(VI) based on 3-digit borrower ZIP	37,311	48.9	20.6	26.0	47.7	78.5

Table 2 (continued)

	N =	Mean	SD	10^{th}	50^{th}	90^{th}
Relationship-weighted interconnectedness:						
(I) based on borrower SIC division	37,311	42.5	27.7	0	48.0	74.4
(II) based on 2-digit borrower SIC	37,311	39.0	26.8	0	41.5	72.6
(III) based on 3-digit borrower SIC	37,311	39.0	27.0	0	40.9	73.2
(IV) based on 4-digit borrower SIC	37,311	39.0	27.1	0	40.9	73.4
(V) based on borrower state	37,311	39.6	26.9	0	43.0	71.9
(VI) based on 3-digit borrower ZIP	37,311	38.1	26.9	0	40.0	72.6

C. Systemic Risk Measures

	N =	Mean	SD	10^{th}	50^{th}	90^{th}
SRISK:						
Systemic capital shortfall (*SRISK*)	5,799	25,744	47,181	-7,427	6,712	89,267
Relative capital shortfall (*SRISK%*)	5,799	2.57	4.16	0	0.62	7.37
Long-run marginal expected shortfall (*LRMES*) (%)	5,799	3.81	2.42	1.82	3.32	6.22
Quasi-market Leverage (%)	5,799	17.98	30.20	5.09	11.01	32.94
CoVaR:						
1% *CoVaR* (%)	1,767	-2.31	1.39	-3.92	-2.05	-0.96
1% *CoVaR* ($bn)	1,767	-15.4	31.3	-49.1	-2.44	-0.24
5% *CoVaR* (%)	1,767	-1.98	1.07	-3.14	-1.82	-0.89
5% *CoVaR* ($bn)	1,767	-12.5	21.9	-44.6	-2.32	-0.18
DIP:						
DIP (€bn)	1,414	14.7	18.6	0.6	6.4	42.2

Table 3: Effect of Distance on Likelihood of Being Chosen As A Syndicate Member

This table reports coefficient estimates from regressions relating the likelihood of a potential lender (that was among lead arrangers in the previous twelve months) being chosen as a syndicate member by the lead arranger to the distance between the potential lender and the lead arranger. The dependent variable is an indicator variable for whether the potential lender is indeed a syndicate member (0 if no and 1 if yes). The independent variable of interest is the distance between the potential lender and the lead arranger based on their portfolios of syndicated loans originated during the previous twelve months. Columns (I)-(VI) use distance as an independent variable based on lender specializations in borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. Control variables include an indicator variable for whether the potential lender has previous relationships with the lead arranger, an indicator variable for whether the potential lender has previous relationships with the borrower, and the market share of the potential lender as a lead arranger in the U.S. syndicated loan market during the previous twelve months. All regressions include loan facility fixed effects. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Syndicate member indicator	(I) SIC Division	(II) 2-digit SIC	(III) 3-digit SIC	(IV) 4-digit SIC	(V) State	(VI)| 3-digit ZIP
Distance from lead arranger	-0.036***	-0.042***	-0.040***	-0.040***	-0.036***	-0.027***
	(0.0010)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0009)
Previous relationship with lead	0.022***	0.020***	0.020***	0.020***	0.022***	0.025***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Previous relationship with borrower	0.534***	0.533***	0.533***	0.533***	0.534***	0.535***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Market share as a lead	0.422***	0.403***	0.405***	0.406***	0.417***	0.434***
	(0.0170)	(0.0173)	(0.0174)	(0.0174)	(0.0175)	(0.0177)
Loan facility fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N =	10,916,818	10,916,818	10,916,818	10,916,818	10,916,751	10,909,897
Adjusted R^2	0.3226	0.3229	0.3228	0.3228	0.3224	0.3220

Table 4: Determinants of Interconnectedness

This table reports coefficient estimates from regressions relating interconnectedness to a number of bank characteristics. Interconnectedness of a lead arranger can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. Bank characteristics include market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, diversification, and the number of specializations the bank is engaged in. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

A. Univariate Regressions

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Bank-level interconnectedness	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip
Regression (I):												
Market share as a lead	1.551***	1.777***	1.800***	1.798***	1.737***	1.387***	2.516***	2.667***	2.741***	2.750***	2.562***	2.552***
	(0.0251)	(0.0289)	(0.0289)	(0.0288)	(0.0289)	(0.0253)	(0.0270)	(0.0274)	(0.0279)	(0.0279)	(0.0280)	(0.0298)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	37,311	37,311	37,311	37,311	37,311	37,311	37,311	37,311	37,311	37,311	37,311	37,311
R^2	0.0601	0.0670	0.0640	0.0629	0.0648	0.0351	0.0638	0.0768	0.0798	0.0797	0.0704	0.0698
Regression (II):												
Diversification	0.499***	0.485***	0.487***	0.487***	0.488***	0.483***	0.609***	0.557***	0.561***	0.560***	0.543***	0.562***
	(0.0020)	(0.0012)	(0.0013)	(0.0014)	(0.0014)	(0.0017)	(0.0080)	(0.0059)	(0.0058)	(0.0057)	(0.0071)	(0.0051)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	36,090	36,090	36,090	36,090	36,017	32,159	36,090	36,090	36,090	36,090	36,017	32,159
R^2	0.8017	0.9539	0.9608	0.9609	0.9300	0.9398	0.4944	0.6127	0.6474	0.6493	0.5547	0.6740

Table 4 (continued)

Bank-level interconnectedness	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip
Regression (III):												
# of specializations	5.685***	1.137***	0.433***	0.294***	1.575***	0.393***	7.163***	1.364***	0.537***	0.371***	1.837***	0.494***
	(0.0184)	(0.0088)	(0.0057)	(0.0050)	(0.0115)	(0.0069)	(0.0840)	(0.0127)	(0.0063)	(0.0056)	(0.0168)	(0.0079)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	36,090	36,090	36,090	36,090	36,017	32,159	36,090	36,090	36,090	36,090	36,017	32,159
R^2	0.6735	0.5274	0.3287	0.2613	0.5705	0.2926	0.4423	0.3705	0.2575	0.2126	0.3738	0.2447

B. Multivariate Regressions

Bank-level interconnectedness	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip
Regression (I):												
Market share as a lead	-0.631***	-1.233***	-1.438***	-1.388***	-1.053***	-1.419***	-0.290***	-0.849***	-1.042***	-0.986***	-0.635***	-0.900***
	(0.0096)	(0.0162)	(0.0133)	(0.0146)	(0.0144)	(0.0218)	(0.0112)	(0.0297)	(0.0247)	(0.0228)	(0.0234)	(0.0205)
Diversification	0.405***	0.431***	0.461***	0.472***	0.432***	0.463***	0.443***	0.481***	0.517***	0.527***	0.460***	0.526***
	(0.0033)	(0.0012)	(0.0010)	(0.0011)	(0.0016)	(0.0014)	(0.0085)	(0.0069)	(0.0061)	(0.0058)	(0.0086)	(0.0050)
# of specializations	1.598***	0.387***	0.169***	0.115***	0.460***	0.160***	2.472***	0.439***	0.191***	0.132***	0.549***	0.165***
	(0.0342)	(0.0070)	(0.0025)	(0.0018)	(0.0093)	(0.0029)	(0.0754)	(0.0139)	(0.0052)	(0.0034)	(0.0186)	(0.0036)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	36,090	36,090	36,090	36,090	36,017	32,159	36,090	36,090	36,090	36,090	36,017	32,159
R^2	0.8133	0.9728	0.9771	0.9750	0.9458	0.9587	0.5043	0.6228	0.6562	0.6569	0.5635	0.6823

Table 4 (continued)

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Bank-level interconnectedness	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit Zip
Regression (II):												
Market share as a lead	-0.647***	-1.261***	-1.584***	-1.579***	-1.024***	-1.460***	-0.047**	-0.729***	-1.061***	-1.060***	-0.457***	-0.907***
	(0.0172)	(0.0141)	(0.0180)	(0.0209)	(0.0155)	(0.0340)	(0.0196)	(0.0271)	(0.0300)	(0.0303)	(0.0219)	(0.0245)
Diversification	0.407***	0.436***	0.464***	0.474***	0.427***	0.478***	0.349***	0.412***	0.445***	0.455***	0.370***	0.456***
	(0.0039)	(0.0009)	(0.0010)	(0.0012)	(0.0013)	(0.0020)	(0.0080)	(0.0053)	(0.0046)	(0.0044)	(0.0067)	(0.0036)
# of specializations	1.467***	0.450***	0.199***	0.140***	0.559***	0.188***	2.233***	0.513***	0.220***	0.155***	0.603***	0.196***
	(0.0522)	(0.0070)	(0.0021)	(0.0017)	(0.0090)	(0.0026)	(0.0704)	(0.0127)	(0.0046)	(0.0033)	(0.0167)	(0.0039)
Lead fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	36,090	36,090	36,090	36,090	36,017	32,159	36,090	36,090	36,090	36,090	36,017	32,159
Adjusted R^2	0.8790	0.9833	0.9855	0.9838	0.9708	0.9746	0.7338	0.8122	0.8301	0.8303	0.7578	0.8443

Table 5: Interconnectedness and Various Systemic Risk Measures

This table reports coefficient estimates from regressions relating a financial institution's systemic risk to its interconnectedness in the U.S. syndicated loan market. The dependent variable is systemic risk, measured by the natural logarithm of systemic capital shortfall (*SRISK*) in Panel A, the natural logarithm of the opposite of 5% *CoVaR* in U.S. dollars in Panel B, and the natural logarithm of the monthly distress insurance premium (*DIP*) in euros. The independent variable of interest is the interconnectedness of a lead arranger, which can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

A. Interconnectedness and *SRISK*

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [*SRISK*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Interconnectedness	0.020***	0.018***	0.017***	0.016***	0.024***	0.014***	0.020***	0.019***	0.018***	0.017***	0.023***	0.016***
	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0016)	(0.0015)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0014)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858
R^2	0.0412	0.0345	0.0312	0.0299	0.0619	0.0225	0.0483	0.0459	0.0444	0.0423	0.0691	0.0363

Table 5 (Continued)

B. Interconnectedness and *CoVaR*

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [– 5% *CoVaR*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Interconnectedness	0.062*** (0.0020)	0.062*** (0.0017)	0.060*** (0.0017)	0.060*** (0.0017)	0.065*** (0.0020)	0.047*** (0.0021)	0.040*** (0.0014)	0.045*** (0.0014)	0.046*** (0.0014)	0.046*** (0.0014)	0.046*** (0.0017)	0.042*** (0.0014)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767	1,767
R^2	0.2443	0.2980	0.3040	0.3022	0.3208	0.1914	0.2319	0.2945	0.3160	0.3174	0.2852	0.2641

C. Interconnectedness and *DIP*

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [*DIP*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Interconnectedness	0.013*** (0.0029)	0.020*** (0.0026)	0.020*** (0.0025)	0.020*** (0.0025)	0.017*** (0.0026)	0.013*** (0.0029)	0.010*** (0.0032)	0.018*** (0.0026)	0.019*** (0.0024)	0.019*** (0.0025)	0.014*** (0.0026)	0.016*** (0.0027)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	1,414	1,414	1,414	1,414	1,414	1,414	1,414	1,414	1,414	1,414	1,414	1,414
R^2	0.0117	0.0314	0.0336	0.0343	0.0215	0.0152	0.0066	0.0272	0.0311	0.0317	0.0160	0.0213

Table 6: Interconnectedness and *SRISK*

This table reports coefficient estimates from regressions relating a financial institution's systemic capital shortfall (*SRISK*) to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the natural logarithm of *SRISK*. The independent variable of interest is the interconnectedness of a lead arranger, which can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. *Recession* is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. *Interconnectedness* × *Recession* is the interaction term of *Interconnectedness* and *Recession*. *European* is an indicator variable equal to 1 if the bank is headquartered in Europe. *Interconnectedness* × *European* is the interaction term of *Interconnectedness* and *European*. Control variables include the natural logarithm of the financial institution's market value of equity and its market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [*SRISK*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
<u>*Regression (I):*</u>												
Interconnectedness	0.010*** (0.0017)	0.007*** (0.0018)	0.004** (0.0018)	0.004** (0.0019)	0.009*** (0.0020)	0.004* (0.0019)	0.007*** (0.0015)	0.005*** (0.0015)	0.004** (0.0015)	0.003** (0.0015)	0.007*** (0.0016)	0.003* (0.0016)
Interconnectedness × Recession	0.009*** (0.0018)	0.009*** (0.0018)	0.009*** (0.0018)	0.009*** (0.0018)	0.009*** (0.0018)	0.009*** (0.0017)	0.009*** (0.0017)	0.010*** (0.0017)	0.010*** (0.0017)	0.010*** (0.0017)	0.010*** (0.0017)	0.010*** (0.0017)
European	1.207*** (0.1284)	1.063*** (0.1287)	0.860*** (0.1305)	0.829*** (0.1314)	0.947*** (0.1444)	0.887*** (0.1609)	1.214*** (0.1251)	1.025*** (0.1161)	0.838*** (0.1161)	0.806*** (0.1159)	0.970*** (0.1291)	0.863*** (0.1337)
Interconnectedness × European	0.003** (0.0017)	0.006*** (0.0017)	0.009*** (0.0017)	0.010*** (0.0017)	0.008*** (0.0018)	0.009*** (0.0021)	0.003* (0.0017)	0.007*** (0.0016)	0.010*** (0.0015)	0.010*** (0.0015)	0.007*** (0.0017)	0.009*** (0.0017)
Ln [market value]	0.474*** (0.0279)	0.474*** (0.0284)	0.477*** (0.0289)	0.478*** (0.0290)	0.459*** (0.0277)	0.504*** (0.0261)	0.496*** (0.0274)	0.488*** (0.0281)	0.481*** (0.0288)	0.483*** (0.0289)	0.477*** (0.0278)	0.503*** (0.0264)
Market share as a lead	0.038*** (0.0058)	0.037*** (0.0059)	0.037*** (0.0059)	0.037*** (0.0059)	0.037*** (0.0058)	0.036*** (0.0059)	0.031*** (0.0060)	0.032*** (0.0060)	0.033*** (0.0060)	0.033*** (0.0060)	0.031*** (0.0058)	0.032*** (0.0058)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858
R^2	0.4244	0.4224	0.4236	0.4236	0.4297	0.4242	0.4230	0.4231	0.4254	0.4252	0.4292	0.4268

Table 6 (Continued)

Ln [*SRISK*]	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Regression (II):												
Interconnectedness	-0.004	0.001	0.001	0.001	0.007*	0.002	0.003	0.006**	0.006**	0.005*	0.011***	0.003
	(0.0030)	(0.0035)	(0.0038)	(0.0039)	(0.0037)	(0.0027)	(0.0021)	(0.0027)	(0.0030)	(0.0031)	(0.0028)	(0.0022)
Interconnectedness × Recession	0.009***	0.010***	0.010***	0.010***	0.009***	0.009***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0017)	(0.0017)	(0.0018)	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
European	–	–	–	–	–	–	–	–	–	–	–	–
Interconnectedness × European	0.018***	0.015***	0.018***	0.018***	0.010***	0.013***	0.007**	0.008***	0.013***	0.013***	0.003	0.012***
	(0.0033)	(0.0033)	(0.0034)	(0.0034)	(0.0033)	(0.0031)	(0.0029)	(0.0032)	(0.0034)	(0.0034)	(0.0034)	(0.0031)
Ln [market value]	-0.063	-0.077	-0.088*	-0.089*	-0.097**	-0.057	-0.051	-0.067	-0.086**	-0.086**	-0.083*	-0.047
	(0.0480)	(0.0482)	(0.0461)	(0.0461)	(0.0451)	(0.0421)	(0.0462)	(0.0448)	(0.0427)	(0.0429)	(0.0430)	(0.0414)
Market share as a lead	0.100***	0.102***	0.100***	0.099***	0.101***	0.100***	0.100***	0.099***	0.097***	0.097***	0.095***	0.098***
	(0.0131)	(0.0133)	(0.0131)	(0.0131)	(0.0130)	(0.0131)	(0.0131)	(0.0131)	(0.0129)	(0.0128)	(0.0127)	(0.0129)
Lead fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858	3,858
Adjusted R^2	0.6734	0.6753	0.6782	0.6781	0.6768	0.6783	0.6747	0.6779	0.6813	0.6810	0.6798	0.6799

Table 7: Interconnectedness and Components of *SRISK*

This table reports coefficient estimates from regressions relating two components of *SRISK* – long-run marginal expected shortfall (*LRMES*) and leverage – to a financial institution's interconnectedness in the U.S. syndicated loan market. The dependent variable is the natural logarithm of *LRMES* in percentage in Panel A and the natural logarithm of the quasi-market leverage ratio (calculated as [book value of assets – book value of equity + market value of equity] as a percentage of market value of equity) in Panel B. The independent variable of interest is the interconnectedness of a lead arranger, which can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. *Recession* is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. *Interconnectedness* × *Recession* is the interaction term of *Interconnectedness* and *Recession*. *European* is an indicator variable equal to 1 if the bank is headquartered in Europe. *Interconnectedness* × *European* is the interaction term of *Interconnectedness* and *European*. Control variables include the natural logarithm of the financial institution's market value of equity and its market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

A. Interconnectedness and Long-run Marginal Expected Shortfall (*LRMES*)

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [*LRMES*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Interconnectedness	0.001	0.003**	0.003***	0.003***	0.007***	0.006***	0.003***	0.004***	0.004***	0.004***	0.004***	0.005***
	(0.0009)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0008)	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)
Interconnectedness × Recession	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)
European	–	–	–	–	–	–	–	–	–	–	–	–
Interconnectedness × European	-0.001	-0.001	0.000	0.000	-0.005***	-0.003**	-0.002	-0.000	-0.000	0.000	-0.001	-0.002
	(0.0015)	(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0015)	(0.0011)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Ln [market value]	-0.193***	-0.199***	-0.203***	-0.203***	-0.202***	-0.191***	-0.183***	-0.189***	-0.195***	-0.195***	-0.187***	-0.181***
	(0.0317)	(0.0320)	(0.0317)	(0.0317)	(0.0311)	(0.0287)	(0.0301)	(0.0301)	(0.0298)	(0.0299)	(0.0300)	(0.0275)
Market share as a lead	0.045***	0.045***	0.045***	0.045***	0.045***	0.045***	0.042***	0.042***	0.042***	0.042***	0.041***	0.041***
	(0.0055)	(0.0054)	(0.0054)	(0.0054)	(0.0052)	(0.0053)	(0.0056)	(0.0055)	(0.0055)	(0.0055)	(0.0055)	(0.0055)
Lead fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	5,796	5,796	5,796	5,796	5,796	5,796	5,796	5,796	5,796	5,796	5,796	5,796
Adjusted R^2	0.3658	0.3680	0.3715	0.3712	0.3818	0.3870	0.3805	0.3807	0.3849	0.3839	0.3827	0.3952

Table 7 (Continued)

B. Interconnectedness and Leverage

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [Levera ge]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Interconnectedness	0.002** (0.0007)	0.001 (0.0008)	0.002** (0.0009)	0.002** (0.0009)	0.004*** (0.0009)	0.003*** (0.0006)	0.003*** (0.0004)	0.003*** (0.0004)	0.004*** (0.0004)	0.004*** (0.0004)	0.003*** (0.0004)	0.004*** (0.0004)
Interconnectedness × Recession	0.004*** (0.0011)	0.004*** (0.0011)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)	0.004*** (0.0010)
European	–	–	–	–	–	–	–	–	–	–	–	–
Interconnectedness × European	0.005*** (0.0012)	0.008*** (0.0012)	0.010*** (0.0012)	0.009*** (0.0012)	0.006*** (0.0010)	0.008*** (0.0013)	0.004*** (0.0010)	0.007*** (0.0011)	0.008*** (0.0011)	0.008*** (0.0011)	0.006*** (0.0012)	0.007*** (0.0012)
Ln [market value]	-0.703*** (0.0428)	-0.709*** (0.0430)	-0.716*** (0.0420)	-0.716*** (0.0420)	-0.714*** (0.0411)	-0.701*** (0.0390)	-0.691*** (0.0416)	-0.699*** (0.0412)	-0.708*** (0.0403)	-0.709*** (0.0403)	-0.699*** (0.0406)	-0.694*** (0.0377)
Market share as a lead	0.071*** (0.0059)	0.071*** (0.0058)	0.070*** (0.0058)	0.070*** (0.0057)	0.070*** (0.0056)	0.070*** (0.0057)	0.069*** (0.0060)	0.069*** (0.0059)	0.068*** (0.0058)	0.068*** (0.0058)	0.068*** (0.0059)	0.067*** (0.0058)
Lead fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	5,799	5,799	5,799	5,799	5,799	5,799	5,799	5,799	5,799	5,799	5,799	5,799
Adjusted R^2	0.8053	0.8070	0.8102	0.8100	0.8100	0.8120	0.8098	0.8124	0.8163	0.8160	0.8115	0.8168

Table 8: Interconnectedness and *CoVaR*

This table reports coefficient estimates from regressions relating a U.S. financial institution's *CoVaR* to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the natural logarithm of the opposite of 5% *CoVaR* in U.S. dollars. The independent variable of interest is the interconnectedness of a lead arranger, which can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. *Recession* is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. *Interconnectedness* × *Recession* is the interaction term of *Interconnectedness* and *Recession*. Control variables include the natural logarithm of the financial institution's market value of equity and its market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [– 5% *CoVaR*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Regression (I):												
Interconnectedness	-0.000	0.000	0.000	0.000	0.001	0.003***	-0.001	-0.001	-0.001	-0.001	-0.000	0.001
	(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0014)	(0.0012)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0011)	(0.0010)
Interconnectedness × Recession	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0021)	(0.0020)	(0.0021)	(0.0021)	(0.0020)	(0.0020)	(0.0021)	(0.0021)
Ln [market value]	1.115***	1.107***	1.107***	1.109***	1.099***	1.089***	1.124***	1.121***	1.120***	1.121***	1.114***	1.112***
	(0.0277)	(0.0278)	(0.0278)	(0.0278)	(0.0298)	(0.0273)	(0.0270)	(0.0270)	(0.0274)	(0.0274)	(0.0273)	(0.0261)
Market share as a lead	0.017***	0.017***	0.017***	0.017***	0.017***	0.018***	0.016***	0.016***	0.016***	0.016***	0.016***	0.015***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0037)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0035)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	833	833	833	833	833	833	833	833	833	833	833	833
R^2	0.8099	0.8094	0.8095	0.8094	0.8103	0.8159	0.8106	0.8091	0.8091	0.8089	0.8105	0.8135

Table 8 (Continued)

Ln [– 5% *CoVaR*]	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Regression (II):												
Interconnectedness	-0.005** (0.0021)	-0.003 (0.0025)	-0.003 (0.0024)	-0.003 (0.0023)	-0.007*** (0.0025)	-0.002 (0.0016)	-0.006*** (0.0012)	-0.006*** (0.0013)	-0.006*** (0.0012)	-0.006*** (0.0012)	-0.005*** (0.0013)	-0.005*** (0.0012)
Interconnectedness × Recession	0.004*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.005*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.004*** (0.0015)	0.005*** (0.0015)
Ln [market value]	0.327*** (0.0963)	0.325*** (0.0954)	0.326*** (0.0952)	0.326*** (0.0950)	0.330*** (0.0958)	0.335*** (0.0983)	0.322*** (0.0941)	0.321*** (0.0943)	0.323*** (0.0939)	0.323*** (0.0939)	0.323*** (0.0957)	0.328*** (0.0944)
Market share as a lead	0.000 (0.0059)	0.001 (0.0058)	0.001 (0.0058)	0.001 (0.0058)	0.000 (0.0060)	0.002 (0.0059)	0.005 (0.0064)	0.005 (0.0065)	0.005 (0.0064)	0.005 (0.0064)	0.004 (0.0063)	0.004 (0.0063)
Lead fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	833	833	833	833	833	833	833	833	833	833	833	833
Adjusted R^2	0.9287	0.9283	0.9284	0.9283	0.9294	0.9289	0.9303	0.9299	0.9300	0.9299	0.9293	0.9298

Table 9: Interconnectedness and *DIP*

This table reports coefficient estimates from regressions relating a European financial institution's *DIP* to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the natural logarithm of the monthly distress insurance premium (*DIP*) in euros. The independent variable of interest is the interconnectedness of a lead arranger, which can be size- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. *Recession* is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. *Interconnectedness* × *Recession* is the interaction term of *Interconnectedness* and *Recession*. Control variables include the natural logarithm of the financial institution's market value of equity and its market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months. Robust standard errors allowing for clustering by month are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
Ln [*DIP*]	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Regression (I):												
Interconnectedness	-0.010***	-0.004	-0.005	-0.005	-0.010***	-0.018***	-0.015***	-0.008**	-0.009***	-0.009***	-0.015***	-0.016***
	(0.0031)	(0.0033)	(0.0034)	(0.0034)	(0.0027)	(0.0037)	(0.0036)	(0.0033)	(0.0032)	(0.0033)	(0.0028)	(0.0038)
Interconnectedness × Recession	0.029***	0.030***	0.030***	0.030***	0.029***	0.029***	0.029***	0.030***	0.030***	0.030***	0.029***	0.030***
	(0.0029)	(0.0030)	(0.0029)	(0.0029)	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0029)	(0.0028)	(0.0028)
Ln [market value]	0.237***	0.195***	0.213***	0.213***	0.256***	0.285***	0.259***	0.229***	0.236***	0.237***	0.282***	0.276***
	(0.0438)	(0.0468)	(0.0474)	(0.0478)	(0.0395)	(0.0406)	(0.0421)	(0.0429)	(0.0433)	(0.0433)	(0.0380)	(0.0399)
Market share as a lead	0.556***	0.519***	0.530***	0.529***	0.556***	0.626***	0.571***	0.543***	0.546***	0.546***	0.581***	0.609***
	(0.0263)	(0.0293)	(0.0321)	(0.0325)	(0.0294)	(0.0384)	(0.0289)	(0.0298)	(0.0324)	(0.0328)	(0.0301)	(0.0396)
Lead fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
N =	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350
R^2	0.2779	0.2735	0.2762	0.2761	0.2776	0.2873	0.2816	0.2744	0.2764	0.2762	0.2817	0.2848

Table 9 (Continued)

Ln [*DIP*]	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Regression (II):												
Interconnectedness	-0.009** (0.0039)	0.001 (0.0043)	0.001 (0.0043)	0.002 (0.0044)	-0.010** (0.0037)	-0.013*** (0.0047)	-0.013*** (0.0042)	-0.006 (0.0047)	-0.003 (0.0047)	-0.003 (0.0047)	-0.010** (0.0045)	-0.013** (0.0051)
Interconnectedness × Recession	0.020*** (0.0027)	0.022*** (0.0027)	0.021*** (0.0027)	0.021*** (0.0027)	0.020*** (0.0027)	0.021*** (0.0026)	0.020*** (0.0025)	0.021*** (0.0026)	0.021*** (0.0026)	0.021*** (0.0026)	0.021*** (0.0026)	0.020*** (0.0026)
Ln [market value]	-1.028*** (0.1220)	-1.036*** (0.1203)	-1.037*** (0.1226)	-1.038*** (0.1232)	-0.999*** (0.1230)	-0.978*** (0.1228)	-1.004*** (0.1227)	-1.004*** (0.1229)	-1.009*** (0.1245)	-1.010*** (0.1249)	-0.979*** (0.1251)	-0.979*** (0.1231)
Market share as a lead	0.853*** (0.0857)	0.870*** (0.0847)	0.864*** (0.0834)	0.864*** (0.0832)	0.865*** (0.0830)	0.869*** (0.0854)	0.850*** (0.0845)	0.866*** (0.0845)	0.864*** (0.0836)	0.864*** (0.0834)	0.868*** (0.0827)	0.874*** (0.0841)
Lead fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350	1,350
Adjusted R^2	0.6474	0.6452	0.6459	0.6458	0.6472	0.6486	0.6478	0.6426	0.6428	0.6428	0.6458	0.6426

Table 10: Interconnectedness and *CATFIN*

This table reports coefficient estimates from regressions relating the aggregate systemic risk, *CATFIN*, to the aggregate interconnectedness in the U.S. syndicated loan market. The dependent variable is *CATFIN* in percentage. The independent variable of interest is the market-aggregate Interconnectedness Index, which can be size- or relationship-weighted and is computed based on distance among lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. *Recession* is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. *Interconnectedness Index* × *Recession* is the interaction term of *Interconnectedness Index* and *Recession*. Control variables in Regression (II) include the natural logarithm of the size (measured by the total amount of loans) and the Herfindahl index of the U.S. syndicated loan market. Robust standard errors are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	Size-weighted Interconnectedness						Relationship-weighted Interconnectedness					
CATFIN	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	State	3-digit ZIP
Regression (I):												
Interconnectedness Index	-1.636***	-1.194***	-1.094***	-1.084***	-1.093***	-0.712***	-0.969***	-0.762***	-0.705***	-0.696***	-0.740***	-0.527***
	(0.1317)	(0.1064)	(0.1005)	(0.0979)	(0.1051)	(0.0642)	(0.0911)	(0.0758)	(0.0723)	(0.0709)	(0.0776)	(0.0548)
Interconnectedness Index × Recession	0.214***	0.238***	0.244***	0.245***	0.266***	0.263***	0.233***	0.245***	0.246***	0.246***	0.261***	0.261***
	(0.0379)	(0.0384)	(0.0389)	(0.0389)	(0.0403)	(0.0411)	(0.0386)	(0.0394)	(0.0394)	(0.0393)	(0.0402)	(0.0408)
N =	252	252	252	252	252	252	252	252	252	252	252	252
R^2	0.4584	0.4420	0.4265	0.4286	0.4218	0.4171	0.4075	0.3990	0.3893	0.3898	0.3885	0.3788
Regression (II):												
Interconnectedness Index	-2.542***	-1.976***	-1.981***	-1.941***	-2.415***	-1.217***	-1.996***	-1.241***	-1.006***	-1.007***	-0.978***	-0.600***
	(0.2818)	(0.2362)	(0.2591)	(0.2483)	(0.3229)	(0.1428)	(0.2879)	(0.2240)	(0.2273)	(0.2195)	(0.2766)	(0.1636)
Interconnectedness Index × Recession	0.158***	0.199***	0.209***	0.214***	0.240***	0.253***	0.217***	0.241***	0.247***	0.247***	0.268***	0.271***
	(0.0375)	(0.0376)	(0.0390)	(0.0391)	(0.0412)	(0.0419)	(0.0408)	(0.0410)	(0.0413)	(0.0411)	(0.0416)	(0.0420)
Ln [market size]	7.856***	8.050***	9.075***	8.720***	12.826***	6.508***	7.753***	4.408*	2.665	2.705	1.753	-0.215
	(2.0952)	(2.2481)	(2.5828)	(2.5167)	(3.0317)	(2.1430)	(2.5843)	(2.5081)	(2.6919)	(2.6367)	(2.9985)	(2.4939)
Herfindahl index	-1.157***	-0.816**	-0.779**	-0.664**	-1.032***	-0.020	0.463	0.349	0.320	0.365	0.327	0.494
	(0.3362)	(0.3260)	(0.3206)	(0.3143)	(0.3227)	(0.2952)	(0.2998)	(0.2991)	(0.3031)	(0.3046)	(0.2972)	(0.3148)
N =	252	252	252	252	252	252	252	252	252	252	252	252
R^2	0.4873	0.4661	0.4505	0.4518	0.4560	0.4333	0.4326	0.4102	0.3950	0.3963	0.3928	0.3842